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Herding and Feedback Trading: An Empirical Investigation

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by Vasileios Kallinterakis

Supervisors: Professor Antonios Antoniou

Professor Phil Holmes

Submitted for the Doctor of Philosophy in Finance

University of Durham

Department of Economics and Finance

Durham Business School

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ABSTRACT

The advent of Behavioural Finance since the 1980s has led to the generation of a voluminous research output pertaining to the behavioural patterns of feedback trading and herding. Previously confined to the realm of popular literature, these patterns of trade have undergone meticulous investigation both in the analytical as well as the empirical dimension. However, it is interesting to note that very little to no attention has been devoted with regards to factors that may bear an impact upon their manifestation. As a result, there seems to be a relative lack of research with regards to the issue of what promotes or inhibits their presence and significance. The thesis present approaches feedback trading and herding in a way that addresses the latter considerations.

Our research first delves into feedback trading through heterogeneous-agents' modeling and demonstrates that the significance of feedback-style trading patterns increases with the diversity of investors' composition in a market. As the latter is an indication of the liberalization of a given market environment (since certain regulatory restrictions are capable of impeding the conduct of trade for various investor-types, especially the overseas ones), we conclude that more liberal market settings are conducive to the relatively more significant manifestation of feedback trading. Our research also provides evidence in favour of the impact of specific regulatory features (capital gains' taxation, short-sales, index futures) upon market-wide herd behaviour across a variety of capital markets. Finally, we focus on the study of herding on behalf of institutional investors and we show how different market conditions as well as the underlying market structures are capable of impacting upon its significance.

As a result, our thesis contributes to the existing literature on herding and feedback trading by studying the impact of a variety of factors upon their significance over time, thus covering an important research gap.

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«ΔΥΝΑΜΙΣ ΠΟΡΙΖΕΤΑΙ ΕΚ ΤΟΥ ΘΕΟΥ»

ΠΛΑΤΩΝ

The thesis present constitutes the outcome of a long, painstaking journey conducted throughout the world of Knowledge and Research and, with the help of God, has reached a conclusion. In this journey a number of people contributed, each and every one in a unique way that helped move it forward.

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Chapter 1

Introduction

The 1980s witnessed the unfolding of certain innovations in the area of Finance, as researchers started to utilize concepts from extra-Finance fields (most notably, Psychology) in order to describe the behaviour of stock prices on the premises of various aspects of investor's behaviour. This culminated into the launch of a research strand that came to be known as Behavioural Finance, which involved the analytical modeling and empirical investigation of several behavioural dimensions regarding investment decision-making that, until then, remained mostly within the realm of the popular Finance literature.

Perhaps the most typical example in this respect is the one related to phenomena of massive investor psychology, often coined through the umbrella-term of “crowd behaviour”. Popular Finance literature (Kindleberger, 1978; Soros, 1987; Galbraith, 1994; Mathiopoulos, 2000) tended to interpret these issues by invoking empirical axioms and observations regarding the human nature. Using those popular concepts as a motivational basis, Behavioural Finance developed two distinct notions to facilitate and systemize the research of such trading patterns; as a result, the terms “feedback trading” and “herding” were introduced. In rough terms, feedback trading refers to trading on the basis of historical prices, while herding to the alignment of one's behaviour to the behaviour of others.

If herding and (positive) feedback trading prevail in a market, then there obviously exists the possibility of large price swings. If a significant number of investors practice positive feedback trading (i.e. buy when prices rise, sell when they fall), it is reasonable to assume that they are capable of exerting a certain pressure over prices that may lead to the development of trends (be they upwards or downwards). Similarly, if herding is widespread among investors, then it would also be expected to exert a certain pressure upon prices towards the direction of the herd. The above imply that both herding and feedback trading have the potential to push prices away from fundamentals. In view of this, we contend that these two concepts raise issues of asset-pricing that are of direct interest to regulators and policymakers alike, as they are able to give rise to abrupt price movements, possibly of destabilizing proportions. They also constitute topics of considerable interest for the investment community, as their presence in the market has the potential of increasing risk (Barberis and Thaler, 2002) through the deviation of prices from fundamentals.

Research on the topics of herding and feedback trading has been undertaken both at the analytical as well as the empirical level and, since the late 1980s, has occupied a considerable portion of Finance-research.

The issue of feedback trading was theoretically addressed initially by De Long et al (1990) inspired by Soros' (1987) intuition of the evolution of trends in the marketplace and was later subject to a rather impressive array of empirical investigations across various market settings (Sentana and Wadhwani, 1992; Koutmos, 1997; Aguirre and Saidi, 1999; Koutmos and Saidi, 2001; Bohl and Reitz, 2004; Antoniou et al, 2005; Bohl and Reitz, 2006). The profitability of feedback trading strategies has been extensively examined in studies related to

either momentum or contrarian (e.g. De Bondt and Thaler, 1985; Bowman and Iverson, 1998; Mun et al, 1999; Jegadeesh and Titman, 2001; Kang et al, 2002; Antoniou et al 2005a) trading. Technical analysis, as a special type of feedback trading, has also received notable attention, with a number of papers (e.g. Bessembinder and Chan, 1995; Ito, 1999; Ratner and Leal, 1999; Wong et al, 2003; Ming et al, 2000; Strozzi and Zaldívar-Comenges, 2005) investigating the profitability of a variety of technical trading rules in several markets. Interdisciplinary, Finance-oriented research, emanating mostly from the wider area of Evolutionary Finance (Farmer, 2002; Farmer and Joshi, 2002; Westerhoff, 2006) has also employed the notion of feedback trading in heterogeneous-agents' models in an effort to replicate certain properties of stock markets (such as, excess volatility, for example).

Herding, on the other hand, has constituted an equally widely researched area. Analytical studies (e.g. Banerjee, 1992; Bikhchandani et al, 1992) illustrate several theoretical possibilities for the manifestation of herd behaviour based upon professional, reputational or psychological considerations. Empirical research in this field has also been on the ascending, with a number of papers trying to measure herding using both aggregate data (Christie and Huang, 1995; Chang et al, 2000; Gleason et al, 2003; Caparelli et al, 2004; Gleason et al, 2004; Hwang and Salmon, 2004; Demirer and Kutan, 2006) as well as microdata (Lakonishok et al, 1992; Grinblatt et al, 1996; Wermers, 1999; Choe et al, 1999; Kim and Wei, 2002a; Kim and Wei, 2002b; Gilmour and Smit, 2002; Voronkova and Bohl, 2005; Wylie, 2005). Most of the above studies have tried to assess the presence of herding in various single-market settings as well as identify its significance

conditional upon certain categorizations, like, for example, which industries or capitalization-groups or fund-categories entail higher herding levels.

Even though the above brief summary on herding and feedback trading indicates the presence of a voluminous research regarding those concepts, it is interesting to note that very little attention has been devoted as to what *promotes* or *inhibits* them. Regarding feedback trading, the only study we are aware of that attempts to touch upon this research issue is the one by Antoniou et al (2005) who test for the impact of the introduction of index-futures upon the feedback trading of the underlying spot markets. As far as herding is concerned, the only studies that try to identify the impact of certain market conditions upon herding are the ones of Gilmour and Smit (2002) and Lobao and Serra (2006) for South African and Portuguese institutional traders respectively.

In view of the aforementioned potential for wider public interest (regulators, policymakers, investors) surrounding these two patterns of trade, it is rather surprising to note that no extensive research effort has been undertaken thus far to investigate the impact of a variety of factors upon their manifestation. Thus, even though most research tends to concentrate upon the impact of these patterns upon the market, the inverse seems to have been largely overlooked both at the comparative (i.e. across markets) as well as at the individual (i.e. within a single market) level.

Given the above, the main research objective of our thesis relates to *addressing the impact of certain market factors upon herding and feedback trading*. As there exists a multiplicity of factors that may promote or inhibit herding and feedback trading, we decided to examine the presence and significance of these two behavioural patterns using selected market factors. It is

our understanding that the choice of factors in our research should not be arbitrary, but rather constitute a function of their relevance to the patterns under investigation. As a result, we elaborate here by noting that our research objective here is to *address the impact upon herding and feedback trading of specific factors, whose relation to those two trading patterns is supported through relevant theoretical frameworks and existing empirical evidence*. Consequently, our research aims at contributing to the empirical literature relative to those behavioural patterns by proposing a novel framework within which their presence can be assessed.

In the interest of gaining deeper insight into the impact of different factors upon herding and feedback trading, we believe that it is beneficial to conduct our tests both at the *single-* as well as the *inter-market level*, so that we may be able to gauge this issue from a comparative viewpoint. To further our understanding of the issue, we contend that the utilization of alternative datatypes (aggregate data as well as microdata) is rather useful in this context. Our work further aims at transcending the empirical dimension of this issue by invoking the *analytical dimension* as well through the proposition of specific novel model-frameworks.

By focusing upon which factors impact favorably or adversely upon herding and feedback trading, our research is of certain relevance to both market participants as well as policymakers alike. With regards to the former, such research is useful both in case one intends to adhere to those behavioural patterns as well as in case one wishes to formulate a strategy of exploiting them across different market settings with variable structures. From a policymaking point of view, our research promotes the discussion over the impact of the regulatory environment over herding and feedback trading, something that has never really

been addressed in the relevant literature. Given the treatment of those two by the popular literature as the culprits underlying abnormal market phenomena, their research on these premises helps delineate whether certain aspects of the market environment itself tend to “grandfather” their manifestation.

Having stated our main research objectives and how we intend to pursue them, we will now provide a short presentation of the following chapters and how they relate to those objectives.

Our thesis begins with a detailed outlining in Chapter 2 of the basic schools of thought that evolved as responses to the Efficient Markets’ Hypothesis (Behavioural Finance, Evolutionary Finance), with our attention then concentrating upon herding and feedback trading both from a theoretical as well as an empirical point of view. Our discussion in Chapter 2 makes it explicitly clear that very little work has been carried out regarding the impact of various market features and conditions upon those patterns across various market-settings over time.

To that end, our research first focuses on feedback trading, a novel type of which we are proposing in Chapter 3. We term that type “threshold-trader”, as its demand function adheres to the feedback-type, yet becomes active anytime a particular threshold has been violated. We insert this type of “conditional” feedback trader within the model-setting proposed by Sentana and Wadhwani (1992); the latter is a bi-trader model accommodating “rational” and “feedback” traders and constitutes the dominant empirical framework for feedback trading

research¹. As a result of this expansion, the heterogeneity of the original model grows, thus including “rational”, “feedback” and “threshold” traders.

Given the above, we choose to test for the presence of this novel trader-type in market environments characterized by varying levels of investors’ heterogeneity. We base the designation of heterogeneity on the premises of the participation levels of various investor-types in a market; more specifically, we consider the degree of heterogeneity of a market to be an increasing function of the participation levels of overseas traders, since it is these traders that are often subject to regulatory restrictions. The idea here is that the less restrictive a regulatory environment is, the wider the investors’ participation will grow, thus expected to allow for more trading strategies to manifest in the market. If so, then our novel type of trader would be expected to manifest itself with greater significance in relatively liberal market environments, a fact confirmed by our empirical findings. Given, however, that regulatory frameworks are subject to change, thus inducing changes in the heterogeneity of the market, we test for the robustness of our findings during periods of “enhanced” and periods of “reduced” market-heterogeneity. Our results seem to suggest that changes in heterogeneity are capable of conferring some impact onto the manifestation of our novel trader-type in relatively liberal market environments only. Finally, we also investigate whether the presence and significance of threshold-traders exhibits differential patterns during turbulent versus non-turbulent market conditions; results from our empirical tests appear to refute this hypothesis.

¹ *The following research on feedback trading is based upon the Sentana and Wadhwani (1992) model framework: Koutmos, 1997; Aguirre and Saidi, 1999; Koutmos and Saidi, 2001; Nikulyak, 2002; Watanabe, 2002; Bohl and Reitz, 2004; Antoniou et al, 2005; Malyar, 2005; Bohl and Reitz, 2006.*

We then proceed towards the investigation of herding in Chapter 4 with the intention of establishing whether specific market features are capable of promoting or inhibiting its significance across markets over time. More specifically, we test for the significance of herding on the premises of the Hwang and Salmon (2004) framework across markets on the basis of: capital gains' taxation, short-sales' constraints and index-futures' introduction. We first acknowledge that the relation between capital gains' taxes and herding is an ambivalent one; in light of strong theoretical (and opposing) arguments regarding the nature of this relation, we test for the hypothesis of herding manifesting itself in significantly different fashions between markets that tax and markets that do not tax capital gains. Our results support our hypothesis, as they indicate that markets where capital gains are taxed tend to produce more persistent herding, which is mostly significantly higher, compared to markets with zero capital-gains' taxes. We then test for the hypothesis that short-sales' constraints would tend to promote herding, in line with the overpricing-rationale put forward by Miller (1977); evidence from markets prior to as well as following the wider introduction of short-sales provide little support for this hypothesis, as they indicate the absence of any impact of their introduction upon herding. Finally, we test for the hypothesis that the introduction of index-futures is capable of producing a significant impact upon herding levels; we base this hypothesis upon the conceptual affiliation between herding and positive feedback trading and recent (Antoniou et al, 2005) findings according to which the introduction of index-futures depresses positive feedback trading in the underlying spot market. Results appear to generate a mixed picture, as the impact upon herding from the

introduction of index-futures does not appear to be uniformly significant across different markets.

In Chapter 5, we study funds managers' herding on the basis of a novel empirical framework. First, we measure institutional herding *exclusively* at the level of the constituents of a market's index in order to gain an accurate picture of it at the index-level. Following that, we condition it upon index-properties associated with market conditions which are capable of bearing an impact upon institutional herding and which have received very little attention in the herding literature. More specifically, we focus upon the impact of: a) market-wide herding, b) trading volume, c) market volatility and d) market-direction upon the herding of institutional investors. To the best of our knowledge, institutional herding has never been studied on these premises combined. Utilizing a unique institutional portfolio-holdings' database from the Portuguese Stock Exchange (Euronext Lisbon), we show that institutional herding at the level of the constituents of the market-index (PSI20) in Portugal is found to be significant irrespective of the market conditions used to test for it. We then illustrate how the highly concentrated structures of both the Portuguese market as well as the Portuguese funds' industry could be employed to explain our findings, since according to Do et al (2006), herding is expected to be higher in more concentrated market settings. Interestingly enough, fund managers in Portugal are found to herd more during relatively non-intense market conditions (reflected here through lower levels of market-wide herding, volume and volatility as well as non-extreme market returns), a fact reconciled with agency-based herding motivations.

Finally, Chapter 6 summarizes our main findings and provides concluding remarks as well as propositions for future research on the issues addressed in this thesis.

Chapter 2

Literature Review

2.1 Introduction

The stock market is an environment where the interactions of various market participants as imprinted in their trading decisions determine the course of securities' prices. Each market operates within the premises of a certain regulatory framework which defines the rules of trading conduct and is implemented and supervised by the respective regulatory authorities (Goodhart et al, 1998). Regulatory provisions are not expected to be identical across markets, as the latter differ in terms of development (Antoniou et al, 1997a). As markets differ in their regulatory settings, they are also expected to exhibit differences in their microstructure, or else "the process and outcomes of exchanging assets under explicit trading rules" (O'Hara, 1997). These differences are bound to affect the trading conduct of investors on several levels: entry (whether, for example, foreigners are allowed to trade), mode (whether, for instance, traders are allowed to sell stocks short-and which ones) as well as treatment (whether, for example, capital gains or dividends are subject to taxation). As a result, the regulatory environment under which a market operates is bound to affect the participation of investors, thus indirectly impacting upon the formation of securities' prices.

The crux underlying much of research in Finance relates to the establishment of a framework of price-behaviour. If the latter can be accurately inferred, then there exists the question as to whether prices can be predicted, in order to devise strategies that can yield profits. However, as mentioned above, the evolution of prices cannot be separated from the evolutionary development of the market and its effect upon its participants. As a result, prices are not the byproduct of an abstract process but are subject to the influence of intertemporal changes in market structure and participation (Shiller, 1984).

Although the changes in market structures can easily be gauged, it is harder to assert their impact upon the behaviour of traders. Even though Finance researchers have attempted to classify traders based upon various premises (e.g. “informed”/“uninformed”, “rational”/“noise”), the reality of the marketplace may actually reflect more complex dynamics (Arthur, 1994). Such complexity is capable of “enriching” investors’ heterogeneity through the constant generation of evolving trading patterns, which in turn, are bound to feed back into securities’ prices (Farmer, 2002).

Recent research in the fields of Behavioural (Barberis et al, 1998; Daniel et al, 1998) and Evolutionary (Farmer, 2002) Finance has attempted to produce conceptual frameworks for the formalization, identification and interpretation of various trading patterns using tools from extra-Finance disciplines, such as Psychology and Biology. The wider availability of micro-databases has facilitated the in-depth examination of such patterns, more so since they often involve data-frequencies that reach down to the minute-level (Griffin et al, 2003).

An important issue here concerns the impact of relevant market features and conditions upon those behavioural patterns. As our previous discussion has

suggested, stock markets are evolving “ecosystems”, where trading strategies are subject to the influence of varying circumstances; consequently, *we would expect different features and conditions of the market environment to bear differential effects upon the manifestation of behavioural trading patterns*. To the best of our knowledge, such an issue has received limited attention in the relevant Finance literature and it is this relatively unexplored area that our work focuses upon.

Two forms of behaviourally motivated trading patterns that have been extensively researched both empirically as well as analytically in Finance are *feedback trading* and *herding*. These two patterns have attracted substantial research attention due to the fact that they are capable of producing collective behavioural dynamics (Bikhchandani and Sharma, 2001) with potentially destabilizing impacts upon securities’ prices (Lakonishok et al, 1992; Wermers, 1999), more so in view of their treatment by the popular Finance literature (Soros, 1987; Galbraith, 1994). Much like with other behavioural patterns, herding and feedback trading have been the subject of very sporadic *ad hoc* research on the premises of differential market-features and conditions.

Our discussion in the present chapter shall first concentrate on a parallel illustration of the basic tenets of the two most influential lines of research in modern Finance, namely the “rational” and the “behavioural” one and explain how the latter endeavours to capture the underlying complexity in the marketplace. The behavioural “camp” in Finance has come to be associated with models reflective of psychological considerations, which are capable of rationalizing several behavioural trading patterns (Barberis and Thaler, 2002); research into the latter has also been at the forefront of recent interdisciplinary research in Finance, generally known as Evolutionary Finance, which will be

delineated in some detail as well. Following that, we shall then direct our focus towards the presentation of *feedback trading* and *herding*. As our previous discussion has indicated, these behaviourally induced trading patterns are capable of generating interesting dynamics in the stock market context, thus enhancing the complexity of the latter. Since the impact of differential market-features and conditions upon the behaviour of these two patterns has not been studied in depth, a study towards that direction would provide us with useful insight into their properties. In view of that, we shall examine these two patterns in detail, with regards to their theoretical foundations and empirical evidence.

2.2 Efficient Markets' Hypothesis and Behavioural Finance: an overview

The term “market efficiency” was first coined in an unpublished work by Harry Roberts (1967), with the seminal study on the area of efficient markets systemizing the theory of the Efficient Markets' Hypothesis (EMH, hereafter) published by Fama (1970). What the EMH essentially posits is that prices fully reflect all relevant information at any point in time over time and that the rate of incorporation of information into prices is instantaneous. In the EMH-world, prices are taken to follow the arrival of news, whose arrival rate, in turn, is considered to be random; thus, prices are assumed to adhere to a random walk. The latter removes the potential for return predictability, thus further ensuring that no investor is able to enjoy abnormal returns through market timing. Investors are assumed to be of a “rational” nature, the latter associated with the appropriate and correct reception, processing and interpretation of information. Put it this way,

traders are assumed to be able to accurately assess any piece of news relevant to a stock. What is more, this theory portrays investors as relatively homogeneous in their expectations, with each one of them maximizing their subjective expected utility and bearing consistent (i.e. “correct”) beliefs as to the distribution of the factors affecting returns (Barberis and Thaler, 2002).

As Fama (1970, 1991) suggested, the issue of market efficiency is not just confined to the question of information-incorporation alone. Claiming that prices are efficient or not is one thing; establishing the “correct” prices is another. Hence, the point needed to be addressed as well is how a stock’s price can be estimated, or else what the appropriate asset-pricing model might be. This dual causality was termed by Fama as the joint-hypothesis problem. The rationale here is quite straightforward: if information is fully reflected in stock prices, then the latter are deemed to be “efficient”. Nevertheless, to be able to assert whether the current price is in line with its “proper” one, it is necessary to have a model that will measure this correctly.

It is perhaps reasonable to assume that the EMH constitutes a rather absolute depiction of the real world. First of all, it is difficult to reconcile this purported rationality with reality, since people differ in terms of background, perception, judgement and financial resources. Being overtly rational is something that is hard to encounter in the market, let alone in life itself. In the end of the day, the term “rational” by itself is subject to various interpretations and may manifest itself in various ways.

Also, whether all investors trade upon the arrival of new information or not is doubtful. Some may see the information and trade immediately, others may stand by in anticipation of more information, others may trade to the opposite

direction from what the information may imply and others might not even trade at all. What's more, it might be the case that an investor submits an order for reasons other than information; they could, for instance, be liquidity traders, in which case their need for cash is not directly affiliated with the information flow. As Fama (1970) and Ross et al (1999), though, acknowledge, not all traders have to agree upon the interpretation of a certain piece of information or respond uniformly to it, as long as those that do, trade in line with the information's content.

Fama's seminal paper triggered a large wave of research that followed various pathways during the 1980s and 1990s; by 1991, Fama had to concede that his 1970-findings had to be partially revised, in particular, the predictability of returns over short (daily and weekly) horizons, in view of more sophisticated computational methods and databases.

The basic tenet of the EMH that came under fire during the subsequent decades was the one pertaining to investors' rationality. This is attributed to the strand of research that came to be known as behavioural finance, which approached this issue through the utilization of concepts related to psychological motivations for trading. What behavioural finance essentially proposed is that investors have to be viewed as less-than-perfectly rational, subject to limitations and biases in both their perception and judgement (Hirshleifer, 2001). Hence, people may not all observe the relevant information to its entirety or even if they do they may perceive it differently, process it differently and, contingent upon it, reach different decisions using heuristics, or else, tools for the simplified processing of complex problems. Heuristics are actually quite sizeable in numbers and their effect over individuals' decision-making cannot readily be estimated; however, their presence has been experimentally confirmed as several studies

illustrate (Tykocinski et al, 2004; Lo et al, 2005). Therefore, the behavioral approach suggests complexity in the market context, with decision-making being subject to factors beyond traditional rationality and with the obvious outcome being that the market starts to appear heterogeneous in content. Behavioral finance captures this heterogeneity by suggesting that investors' beliefs, expectations and processing abilities are different. Due to those differences, the response of traders to news and/or events is not expected to be symmetric; indeed, investors may react excessively ("overreact") or with a delay ("underreact"). This purportedly biased response may in turn result in mispricing, where the actual return of a stock deviates from its fundamental one. Such over- and underreaction patterns have constituted the cornerstone of much of the research undertaken by behaviorists, in an attempt to show that prices are prone to certain patterns following given events and that they may be profitably exploited by those who are aware of them.

A rather large portion of research in behavioural Finance has been devoted to the study of "contrarian" and "momentum" strategies aiming at exploiting the purported over/underreaction patterns across markets. A number of studies (De Bondt and Thaler, 1985; Bowman and Iverson, 1998; Mun et al, 1999; Jegadeesh and Titman, 2001; Kang et al, 2002; Antoniou et al 2005a) have investigated whether such strategies can be profitable in a variety of market settings and whether the observed profits can be attributed to investors' over/underreaction. Results from such research seem to affirm the potential for profitability from the implementation of such trading strategies.

An impressive array of research into the documented "anomalies" has been devoted to the study of "seasonalities", the latter referring to empirically

observed patterns of prices during specific temporal periods. These may include specific: a) months, such as the “January-effect” (Lucey and Whelan, 2004), the “September-effect” (Reutter et al, 2002) and the “Mark-Twain-effect”(Balaban . 1995); b) days of the week such as the “twist-of-the-Monday-effect” (Leal and Madureira, 2001), the “day-of-the-week” effect (Kiymaz and Berument, 2001) and the “holiday-effect” (Lau and McInish, 2002); c) other subdivisions of the year, such as the “semi-monthly-effect” (Balaban and Bulu, 1996). It follows that a trader in possession of the knowledge of those patterns may choose to employ them to generate profits that others could not. This, however, could run counter to the spirit of the EMH, which essentially claims that such patterns do not exist (Fama, 1970) and that even if they do, they cannot be profitably exploited due to transaction-costs (Fama, 1991). Coutts and Sheikh (2002) document the absence of elsewhere reported anomalies (weekend-, January- and Pre-Holiday-effect) in the All Gold Index of the Johannesburg Stock Exchange between 1987 and 1997, which they attribute to microstructure features of the South African market. Gregoriou et al (2004) report evidence of the Monday-effect for the FTSE 100 over an 11-year period (1986-1997) and find that this purported anomaly seems to wane off when transaction costs (proxied by the bid-ask spread) are taken into account.

An anomaly that has been very often cited is the size-effect. The latter refers to abnormal returns observed for small capitalization stocks and has surfaced in a series of research studies. For example, the size-effect seems to be associated with herding (Lakonishok et al, 1992; Wermers, 1999), analysts’ forecasts (Kiymaz, 2002), technical analysis (Antoniou et al, 1997b), IPOs

(Kiymaz, 2000), price-limits (Kim and Limpaphayom, 2000) and informed trading (Easley et al, 1996).

However, even though behavioural finance has put forward a series of psychological explanations to account for certain perceived patterns in price-behaviour, it has yet to come up with a unified model of price-formation (Hirshleifer, 2001; Brav and Heaton, 2002). As Fama (1970) has pointed out, every test of market efficiency must be accompanied by the test of a relevant asset-pricing model (“joint-hypotheses” problem). To be able to tell whether the price of a security at any point in time equals its fundamental value contingent upon the amount of information available, one has to use the appropriate discount rate for its expected cash flows, which in turn requires an appropriate discount model. The problem with behavioral finance is that no such model has been put forward so far, whilst many of the inefficiencies it claims to have unveiled have been empirically questioned.

What is more, most behavioural research tests the impact of a bias or two (Barberis et al 1998; Daniel et al, 2001) over traders’ behaviour while ignoring other biases, thus leaving the possibility of alternative explanations open. Since the number of possible biases is unknown, it is hard to: a) assess the impact of each one over each trader separately and all of them as a whole and b) assess the impact of the possible interaction of those biases upon investors’ behaviour. In short, behavioural finance seems to amplify the very ambiguity it is endeavouring to explain, since the vastness of psychological biases renders their study less than perfectly feasible and their applicability questionable. In his main criticism against the behaviorists, Fama (1998) stresses the fact that the majority of the reported anomalies appear to be figments of methodological flaws, including

sample biases and return metrics, while again (as in his 1991-paper) he emphasizes that the size-effect is to account for a number of those. Hence, he posits that the purported price-patterns around certain events are not as significant as the behaviorists initially proposed.

The main contribution, however, on behalf of the behavioural Finance is the study of the nature, role and impact of traders that do not necessarily adhere to purely rational patterns. In Finance, researchers have termed these less-than-perfectly rational traders as “noise traders”, the implication here being that they do not trade on information but rather on “noise”; the latter is taken to include anything that is not relevant to the fundamental value of a stock. If noise trading assumes a certain size in the market, then it is bound to bear an impact on returns, possibly leading them to deviate from their fundamental value. Thus, noise traders are capable of inducing mispricing (De Long et al, 1990), since they are not adhering to the EMH-postulates and the accompanying risk in such cases is known as “noise trader risk” (Barberis and Thaler, 2002).

The latter constitutes a tangible obstacle to arbitrage, since the presumed presence of noise traders is expected to render arbitrage costly. Assume stocks A and B being two perfect substitutes and assume that stock A’s price is falling due to noise trading. Then the rational investor may opt for going short on stock B (rational arbitrage) in order to alleviate the effects of the price fall. In the presence of noise traders, however, it might be the case that the price continues its fall and that the substitute they have gone short on may not suffice to protect them from the degree of this fall. Hence, perfect substitutes (assuming that they exist) may not be particularly useful for the rational investor in case noise traders have an amplified presence in the market. The latter implies the existence of “limits” to

arbitrage (Shleifer and Vishny, 1997) and suggests that under less-than-perfectly rational circumstances, arbitrage might not be possible and, if prolonged, may also prove costly. Barberis and Thaler (2002) also mention a number of other types of risk that come hand in hand with noise trader risk, namely horizon risk (when transaction costs eliminate profits due to the persistence of mispricing) and synchronization risk (when the mispricing is so large that requires the participation of a sufficient number of arbitrageurs to counter it).

Noise traders are thus associated with uncertainty in the market, even though one might expect them to be the source of profit for rational traders (Wang, 2002). The problem here is that rational traders can only assume a limited amount of risk-exposure; hence, if the market grows riskier than their status can possibly accept, they may well decide to unload their positions. Kyle and Wang (1997), for instance, find that in an imperfectly competitive securities' market, irrational (in the sense of overconfident) traders may be able to "intimidate" their competing informed counterparts. An alternative scenario, however, might involve rational investors jumping onto the bandwagon of the trend in order to take advantage of the purported mispricing (De Long et al, 1990; Andergassen, 2003).

An assumption tested by many authors is that noise trading is more pronounced in developing markets, which are only beginning to operate and whose relative regulatory framework is either absent or incomplete. In the presence of regulatory loopholes, we may expect to come across adverse phenomena, such as manipulation (Allen and Gale, 1992; Mei et al, 2004),

rumour-mongering² (Van Bommel, 2003), Ponzi-games (Goodhart et al, 1998; Sadiraj et Schram, 1998) and insider trading. It follows that there is more ambiguity surrounding those markets in terms of information quality, a fact compromising the efficiency of these markets. The deficiencies witnessed in emerging markets are frequently compounded by the fact that the initial regulatory framework may include specific provisions pertaining to the rules of investors' participation in the market. These could include restrictions relative to the amount of foreign capital invested, the foreign-shareholding percentage allowed, or the stocks available to non-indigenous investors. Such a situation can deter foreigners from entering the market, thus indirectly "grandfathering" limited participation with all adverse effects accruing, e.g. "local" insider trading, easier control of the market by a few indigenous informed traders at the expense of the "uninformed" ones et al. The prohibition of certain trading practices, such as, for example, short-selling, may also lead to distortions of the price-formation process and facilitate mispricing (Miller, 1977).

However, as Antoniou et al (1997a) demonstrate in the case of Turkey, an emerging market is not destined to remain in that status forever. As emerging capital markets undergo a process of liberalization, previous barriers to entry or restrictions to trading may be loosened or abolished, thus allowing for increased (especially overseas) investors' participation. Such a development allows for the local pool of information to grow, as the increase in the flow of trades from more traders will incorporate their information, which may eventually lead to greater

² *The importance attributed to rumours can also be gauged through the Rumour and Rumour Mongering Prohibition and Punishment Law of the State of Zamfara in Nigeria. According to that Law, "anybody caught making statements or assertions of doubtful accuracy" or giving reports that could not be "instantly verified", would be committing an "arrestable offence, punishable immediately with 40 strokes of the cane". It is worth noting, however, that the above Law was not applicable to journalists-and politicians (Source: <http://www.foolscap-media.com>).*

informational efficiency. Similar results are provided by Holmes and Wong (2001) relative to the volatility of prices in Asian markets prior to and after their liberalization process and by Balbina and Martins (2002) for seasonal anomalies prior to and after the upgrading of the Portuguese market to “developed”.

We have thus far outlined the fundamental tenets of the two major lines regarding research in the behaviour of stock returns, namely the EMH and behavioural finance. However, behavioural finance is not the sole strand of research countering the lines of the EMH. Recent interdisciplinary studies (Farmer and Lo, 1999) have given rise to what has come to be known as “evolutionary finance”; the latter constitutes a stream of research that accommodates various schools of thought (such as agent-based modeling and econophysics) and advocates viewing the market as an ecosystem where many different “species” interact with each other through their trading strategies. Hence, in evolutionary finance, agents with various strategies behave like species in nature, i.e. they compete for their survival in the marketplace (Arthur, 1997; Arthur, 1999, Arthur, 2000a; Arthur, 2000b; Farmer, 2001; Farmer, 2002; Farmer and Joshi, 2002, Mauboussin, 2002). To achieve that, they have to ensure that their trading tactics are continuously adapted in view of the ever-changing circumstances.

In the “evolutionary” framework, the market is characterized by complexity, thus rendering the rational processing of information difficult. To counter this problem, investors may choose to resort to “inductive reasoning” (Arthur, 1994). The latter is relevant to the employment of “heuristics” we spoke of before and implies that each investor devises a number of patterns in his mind when trading, which are subject to continuous assessment. Thus, following each

trade, he evaluates their profitability and updates them accordingly (maintain the successful ones, discard the unsuccessful ones, modify others and introduce perhaps a few new ones). This process is assumed to be continuous, so that each investor in the end is seen as an ever-evolving behavioral entity in a pool of other such. Hence, the world of the stock market is not just “complex” (due to investors’ heterogeneity), but also “evolutionary”, given the evolution of new market outcomes following the intertemporal syntheses of the various strategies of interactively trading agents. Each new situation leads to adaptation, new feedback, new processing, new decisions, new investment, new prices and again new adaptation, with the cycle simply repeating itself while generating new outcomes. Mauboussin (2002) has taken one step ahead to suggest that this interactive heterogeneity in the stock market reflects the “invisible hand” of Adam Smith.

As Farmer (2001) has suggested, the field of evolutionary finance (and the affiliate one of agent-based modeling) is still in their infancy-stage. However, the fact remains that these schools of thought have stimulated research, especially from scientists beyond the Finance-field, such as Mathematics, Physics and Biology; the outcome so far has been an array of models that attempt to describe market outcomes in a novel way. This area has evolved into a rather productive research field with a series of scholars developing quantitative models based upon extra-Finance concepts designed to capture and describe the evolution of certain market phenomena. The latter include return-predictability (Strozzi and Zaldívar-Comenges, 2005), bubbles and crashes (Lux, 1995; Johansen and Sornette, 2000; Mansilla, 2001; Focardi et al; 2002), nonlinearities and excess volatility (Lux and Marchesi, 1998; Iori, 2000; Matassini and Franci, 2001; Górski et al, 2002; Iori, 2002; Strozzi et al. 2002; Kyrtsou and Terraza, 2002; 2003a; 2003b; 2004;

Belaire-Franch, 2004; Cross et al, 2004) and herding (Cont and Bouchaud, 2000; Eguiluz and Zimmermann, 2000; Xie et al, 2002; Rodgers and Zheng, 2002; Wagner, 2003). Thus, evolutionary Finance has started to assume a frontline position in Finance research, more so in view of advanced quantitative techniques that allow novel insights into price-behaviour. However, much like what has been noted above about behavioural Finance, the field of evolutionary Finance has not yet managed to agree upon a single model to describe price-formation (Hirshleifer, 2001). Nevertheless, its contribution rests upon the fact that it has stimulated non-Finance researchers to investigate financial issues through their very scientific premises, thus opening up new pathways for existing Finance-research.

Our discussion has, therefore, presented the basic arguments surrounding securities' return-behaviour as delineated both by the Efficient Markets' Hypothesis and behavioural Finance. As the above discussion indicates, there appears to exist complexity in the marketplace, which may manifest itself in multiple fashions. The latter, as we have seen, have been investigated from both socio-psychological (behavioural Finance) as well as evolutionary angles (agent-based modeling). The introduction of extra-Finance concepts into Finance (e.g. psychology, biology) has provided us with new insights into the behaviour of prices by endowing us with an arsenal of novel approaches and interpretations. These advances in financial research, coupled with the advancement in financial databases, have rendered it possible to identify specific patterns of trading behaviour that previously existed in the realm of analytical modeling and test for them empirically.

Our research aims at studying two such types of trading behaviour, namely feedback trading and herding. The former pertains to investors trading on the basis of historical prices, while the latter is founded upon investors' interactive imitation. These behavioural patterns have been investigated rather extensively in the Finance literature (with findings emanating from both the “behavioural” as well as the “evolutionary” strands) and we shall have a chance to witness a more detailed presentation of them in the following sections.

2.3 Feedback Trading

2.3.1 Definition, Sources and Motivations

The concept of feedback trading relates to investors extrapolating from past price patterns (actual or perceived ones). If investors trade in the direction of those patterns, they are taken to be positive feedback trading; conversely, if they trade to the opposite direction, they are coined as “contrarians” (negative feedback traders). Whether feedback trading is positive or negative, its very foundations lie in the perception that prices maintain some sort of inertia in the market (Farmer, 2002), in the sense that they tend to produce directional patterns (trends) for certain periods of time. This very perception may be rooted in a variety of considerations, as we shall soon denote. Suffice to say for the moment, that, although feedback trading is price-based, there is little agreement as to its practice: people do not use past prices the same way. The above also indicates that irrespective of its mode, feedback trading *per se* appears to run counter to the

efficient markets' hypothesis. since its practice is based upon the recognition and possible exploitation of perceived price patterns.

We shall now turn to the main sources and motivations underlying the concept and practice of feedback trading.

2.3.1a Behavioural grounds

As has been noted before, investors have been found to be prone to certain biases, i.e. judgemental errors that may impede the accurate processing of the received information. In short, they may witness signals in the market, yet fail to correctly interpret them. Sometimes, this is due to the nature of things that may promote uncertainty by itself; a single explanation may not be available, or the whole picture may be hard to understand (e.g. because of lack of special knowledge). Alternatively, this might be because of the fact that each person sees things under his own angle and tries to interpret them in a manner that would suit his purpose, whatever that might be. Feedback trading has the tendency to simplify things by narrowing decision-making to the study of historical price-behaviour. Thus, a feedback trader, need look no further than past prices to conduct his trades.

Feedback trading is also motivated through data-availability, since historical data on prices are easy to find in the financial press (see Huddart et al. 2002), while more sophisticated data are harder to obtain. Further to that, the simplified analysis of such data (as carried out mostly by technical analysts in the press) facilitates the communication of these "technical heuristics" to a wider audience, which is perhaps not typified by a sufficient educational background or investment experience. Hence, if an investor is unable to perform any other form

of securities' analysis, searching for patterns through *technical analysis* may serve as some kind of substitute to this end and constitutes a primary justification of feedback trading. This is very relevant to what we mentioned previously about inductive reasoning, as resorting to feedback-patterns can prove a potentially useful (and "easy-to-use") tool in a complex market environment.

We shall now deal with some of the biases that have been documented so far in the behavioural Finance literature in order to show how these might be affiliate to feedback trading.

As Barberis et al (1998) showed feedback trading can be reinforced through the joint presence of two biases, namely, the *representativeness heuristic* and the *conservatism-bias*. In their model, they assume that there exists a single source of information, namely earnings' announcements, which are reported every period; earnings are presumed here to follow a random walk. The authors also assume that there exists a "*representative*" investor, who perceives earnings as subscribing to either of the following "regimes": *mean-reverting* or *trending*. The investor's judgement as to which regime earnings belong in each period is taken to be a function of the exact previous period's earnings' announcement. As a result, this conjectural investor-type trades on the basis of perceived earnings' trends.

If the earnings' announcement for period t is co-directional to the earnings' announcement for period $t-1$ (i.e. is of the same direction as in period $t-1$), then this is taken to signify a continuation of the past period's earnings' trend, thus leading the investor to posit that the earnings are under the *trending* regime. If so, then Barberis et al (1998) argue that the investor is under the influence of the *representativeness heuristic*, which refers to the individual drawing

conclusions about a general population by overweighting a sample of recent observations and considering it as representative of its properties. The *representativeness heuristic* can, thus lead investors towards chasing (actual or hypothetical) trends following a series of directional price-movements and as such can be viewed as a factor facilitating “price-overreaction”.

Alternatively, if the earnings’ announcement for period t is counter-directional to the earnings’ announcement for period $t-1$ (i.e. of the opposite direction compared to period $t-1$), then this is taken to signify a sign of reversal of the past period’s earnings’ trend, thus leading the investor to posit that the earnings are under the *mean-reverting* regime. However, as Barberis et al (1998) argue, the investor may not respond instantly to the arrival of counter-directional signals, in anticipation of their continuation; in other words, given the representativeness heuristic, the investor would expect more than a single antithetical signal to change his perception as to the earnings’ regime. The authors ascribe this to the influence of the *conservatism bias*, which refers to the slow updating of beliefs in light of new evidence. The *conservatism bias* can, thus lead investors towards delayed responses to newly arriving signals and as such can be viewed as a factor facilitating “price-underreaction”.

Thus, Barberis et al (1998) illustrate how an investor may practice feedback trading in the presence of the interplay between the representativeness heuristic and the conservatism bias. If recent evidence makes one believe that a stock is moving towards a certain direction without taking anything else into account, then obviously one narrows the problem down to something that is convenient for him (or his judgement), either because it is perceptively appealing to him (easier to understand) or because he does not have the time or the ability to

process more information. If this price-performance persists, then he may as well assume that a trend is, indeed, at work and this may well suit his purpose for the very same perceptive reasons. The Barberis et al (1998) model seems to provide us with an initial theoretical paradigm of feedback trading, more specifically *positive* feedback trading, as the biases to which the “representative” investor adheres suggest trading towards the direction of the trend.

Overconfidence (Odean, 1998) as a bias is also relevant with respect to positive feedback trading; if one were to follow a certain pattern of trading and events were to confirm its credibility, then one would have every reason to feel overtly “proud” as to the fact that his “mode” of trading is the “right” one. Suppose one observes a price-rise of a stock and suppose that this continues for some time. A positive feedback trader would be expected to buy the stock in anticipation of a further rise in its price. Let us now assume that this is indeed the case and that the price of the stock increases even more. By now, our hypothetical investor has a series of reasons to experience some euphoria. First of all, he bought in view of the price-rise, hence, he may consider himself as possessing good foresight (“*self-attribution*” bias; see Barberis and Thaler, 2002), thus overestimating his actual stock-picking abilities. Secondly, if he sees the price continuing its ascending route, he may view this as a sign that other people are buying as well, hence the stock must be “good”. This is reminiscent of an old adage according to which “people buy because prices go up and prices go up because people buy” (Mathiopoulos, 2000). As a result, this may lead him to believe (ex post) that he had somehow managed to predict this development before it even occurred. The latter is known as “*hindsight-bias*” (Barberis and Thaler, 2002) and, if dominant, is expected to furnish him with the belief that he is

able to predict the future as well-thus boosting his purported overconfidence. Thus, the overconfidence-bias can lead to more aggressive trading (Odean, 1998) and as such can reinforce existing positive feedback trading tendencies.

Although the above behavioural explanations may seem more adjacent to the case of positive feedback trading, negative feedback trading can also be addressed behaviourally. Shefrin and Statman (1985) have shown that people may be less reluctant to sell stocks that have recently performed well and hold onto those, whose performance has been poor, a behaviour which they have termed as the “*disposition effect*”. Reasons here seem to vary. People may sell “winner” stocks in anticipation of mean-reversion and keep “loser” stocks in anticipation of a price-rebound; they may also do so because it is more “painful” for them to realize losses than gains (Leal et al, 2006).

Thus, behavioural reasons may lead investors to adopt feedback trading as a tool for investment purposes. However, as we shall see next, it may be the case that a trader uses feedback strategies in order to take advantage of those biases of other traders.

2.3.1.b Rational speculation

Feedback trading need not be restricted to “noise” traders who may be susceptible to behavioural biases, maintain less abilities/resources or use technical analysis. Rational traders may themselves employ trading rules based on historical prices if they feel they have to protect their positions against (or take advantage of) abrupt market movements; portfolio insurance (Luskin, 1988) and stop-loss orders (Osler, 2002) are relevant here. Such strategic choices on behalf of rational traders are founded upon the belief that noise traders might push prices away from

their fundamental value, thus leading to a mispricing of indefinite duration and magnitude (see Barberis and Thaler, 2002).

We will first examine the case of rational speculators employing price-based trading strategies based on the anticipated feedback trading of noise investors. De Long et al (1990) assume a model where rational speculators are assumed to know that information relative to a stock's fundamentals is to be announced some time in the future and, at present, they receive a signal representative of that information. If the content of this signal is indicative of a rise of the stock's price in the future, they decide to buy the stock now and sell it prior to the information going public (i.e. prior to the anticipated positive response of prices to it). However, in due course, they realize that a significant part of the investors' population is beginning to follow their trades as time goes by; thus, as the speculators start buying the stock, "noise" traders follow suit (they buy as well), thus engaging in positive feedback trading and prices begin to deviate from fundamentals. The prevalent consideration for the noise traders is to participate in what they foresee as a trend with the potential for profits, since the price exhibits positive signs persistently. When the speculators start observing this, they try to exploit it, initially by selling when the information expected is announced and then by going short on that stock in anticipation of a price-reversal. De Long et al (1990) contend that this behaviour of the speculators is actually pushing prices away from fundamentals, as they first help launch a trend, which they then try to exploit. Similar to this, Andergassen (2003) shows that rational speculators may prefer to lure noise traders into a trend-chase, before fundamentals become public knowledge. As a result, the above papers depict a special case of feedback trading: rational traders engage in "forward-looking" feedback trading by devising price-

based trading rules based upon the anticipated response of noise traders to the announcement of fundamentals in the future.

The above case is a formal identification of what George Soros (1987) termed “reflexivity” in the market, which implies the existence of a “reflexive” relationship between stock prices and fundamentals. Soros noted that the key to such a relationship is the “trend” in the market, which he decomposed into the “underlying trend” (what fundamentals suggest about the value of a stock) and the “prevailing bias” (whether investors’ mood is tilted towards buying or selling). Thus, if fundamentals hint towards positive prospects for a stock, this will constitute the stock’s “underlying trend”; however, for that to be reflected into stock prices, it is necessary to be “communicated” to the wider public (“cognitive function”). If investors are convinced about these prospects, the next step is to “participate” in them by actively directing their purchases towards that stock (“participating function”). From then on, a self-reinforcing process sets off, where, the prospects of the stock (as determined by fundamentals) gradually become subject to the influence of stock prices, as more and more investors buy into that stock. Thus, in a certain sense, stock prices confirm (are “*reflective*” of) the fundamentals (after all, the assumption was that the prospects of the stock looked good) and feed back (“*reflect*”) onto them (people’s perceptions of the stock’s fundamental value are now positively influenced by the continuous rise of the price itself), something that Soros termed as “market reciprocity” (Soros, 1987). With the “prevailing bias” being positive (i.e. with people buying), the price rise is expected to accelerate up to the point where it can no longer accommodate such ever-rising expectations. Thus, Soros’ description of his investment strategy constitutes an eloquent illustration of the analytical

presentation of De Long et al (1990), who admit using Soros' trading pattern as a motivation in their work.

Hence, what De Long et al (1990) theoretically propose and Soros (1987) empirically illustrates is the possibility of "rational" traders trading on the price-trend which they induced in the first place; here, "rational" traders are taking advantage of their informational superiority as well as the anticipated behavioural response of their "feedback" counterparts. Thus, although rational speculators do not operate on the basis of a feedback-style function, they choose to follow a price-based trading conduct, since their information indicates that it is "rationally" beneficial for them to do so.

However, the pattern of rational traders may assume a feedback form itself if they choose to use their informational leverage to profit from mispricing, without having induced any trend in the first place. Farmer (2002) and Farmer and Joshi (2002) assume that there exist rational traders who are trading upon the fundamental value of a stock and who are, thus able to estimate the deviations of its price from fundamentals. If so, they may choose to take advantage of this mispricing in order to enter/exit the market before the mispricing becomes excessive, by utilizing threshold-based trading rules. The latter involve trading on the "mispricing" up until the pre-determined thresholds indicate that it is profitable for them to do so. This can be associated with the employment of "stop-loss" orders and portfolio insurance strategies and can be justified on the grounds of keeping the number of transactions (and the associated costs) to a minimum.

2.3.1c Informational asymmetry

Feedback trading can be taken to be a strategy of risk-aversion, as it may be employed on occasions when a trader is faced with an-actual or perceived-asymmetry of information in a market. This may be the case of an investor trading in a foreign market or in stocks for which he knows little. In either case, he might choose this type of strategy if he senses himself being at an informational disadvantage.

Brennan and Cao (1997) report substantial positive feedback trading on behalf of US funds when investing in both developed and emerging markets, a fact they attribute to the perceived asymmetry in information between them and their local counterparts. However, non-US investors seem to face little informational asymmetry, if at all, when trading in the US, which is evident from the differential trading strategies they utilize. Kim and Wei (2002a; 2002b) also report similar evidence for overseas traders in the Korean market while Yang (2002) documents negative feedback trading on behalf of foreign funds for the Taiwanese stock market.

It is not easy to assert how realistic such an assumption might be for large institutional investors who maintain close ties to the markets in which they invest. It is perhaps difficult to imagine a large US fund, for instance, following the trend simply out of fear of the local investors and their purported “privileged” access to information. It would perhaps be more realistic to seek such trading considerations in cases of smaller institutions or even individual investors that reside overseas and who might be in such a cumbersome situation in terms of asymmetry (again this is a hypothesis pending proof).

Informational asymmetry can also be fuelled by the aforementioned size-effect. Easley et al (1996) present a model showing that the probability of informed trading is larger for small capitalization stocks relative to larger ones. The rationale here seems to be the following: Smaller stocks often represent a predicament due to the limited coverage they enjoy. What's more, most information about them is of firm-specific nature, which only further compounds the ambiguity surrounding them. Given this nature of small capitalization stocks, any trade concerning those is bound to raise questions: since information about those stocks is mostly of idiosyncratic nature, then those trading must have access to it. Contrary to market-wide information, firm-specific information is more difficult to acquire, notwithstanding the fact that its quality might be more difficult to assess (it may well be a floating rumour designed to attract attention). Evidence (Lakonishok et al, 1992; Wermers, 1999; Voronkova and Bohl, 2005) shows that fund managers are more prone to engaging in positive feedback trading when dealing with small-capitalization stocks, a phenomenon attributed to the aforementioned nature of those stocks. Since these stocks are less known, a fund manager might prefer to follow the trend with respect to those stocks rather than go-it-alone.

2.3.1.d Manipulation

The term manipulation refers to the attempt by an individual or a group of individuals to influence the price of a stock to their benefit. It is an effort that entails the element of intent specifically directed at "fixing" a desirable market outcome. Economic sense suggests that, much like with any other commodity, this is possible through the influence of the demand/supply of the stock. Stock market

practice has so far provided us with a number of patterns of manipulative intent, such as “ghosting” (when two or more market makers engage in collusive conduct), “spoofing” (the placement of large orders through an Electronics Communication Network-ECN) and “scalping” (intraday trading leading to small gains). Manipulation has the potential to generate trend-chasing (positive feedback trading) and it is this issue that we shall now explore.

Van Bommel (2003) refers to the practice of “pump and dump” relative to stocks, which is tantamount to what Allen and Gale (1992) call “information-based manipulation”. We shall present a simple version of a manipulative scheme of that sort. The rationale here is notably straight (Mathiopoulos, 2000; Kolmer, 2001): an individual (or a group of individuals) pinpoints a stock, which for some reason has attracted little attention so far or is little known to the wider public. The latter might not always be the case, but is vital to the extent that it raises the levels of uncertainty surrounding that stock. The limited dispersion of the stock’s shareholder-ownership is important, albeit not necessary; however, the smaller the dispersion, the easier it is for the price to be cornered (a small number of shares is more easily controllable compared to a large one).

What these “manipulators” essentially do is to start disseminating favorable news relative to that stock in order to fuel investors’ demand. This could be arranged either through a number of financial analysts that agree to publish positive comments for the stock or through the dispersion of anonymous rumours in the marketplace. Whichever the combination might be, the important thing is that the stock is beginning to reflect a positive picture to the public, thus calling for its attention. Whether the owner of the underlying company is party to this scheme remains an open question. Presumably, his connivance (active-through

assisting the maintenance of the price at certain levels-or silent-by pretending ignorance to what is taking place) is quintessential to the success of the endeavor.

In practice things are conjectured to follow this route: as soon as the price rises, people witness a price-continuation of an ascending nature. Some of them will opt for buying the stock, thus boosting its price even higher. As the argument often goes, more people will be tempted to follow suit, since the stock seems a profitable opportunity. As time goes by, more people buy the stock and its price rises even further. When the price reaches a certain “threshold” (pre-determined or not), those behind the manipulative scheme may choose to sell. Their sales are presumed to exert a certain pressure on the stock’s price, thus providing the impression to the others that a decline is starting to materialize; if so, they will choose to sell as well. This will eventually lead to the price’s depression. As a result, information-based manipulation is based upon positive feedback trading, since its aim is to get people to follow the perceived “trend”.

Another type of manipulation that Allen and Gale (1992) have analysed is the so-called trade-based manipulation (see also Mei et al. 2004). According to this, an uninformed trader follows the trades of another trader whom he knows to be informed. Assuming that the informed trader sets the pace for the price of a stock, the trade-based counterpart of his, tries to infer the information he possesses by copying his trades. The case of trade-based manipulation may be encountered in circumstances where an investor reads in a bulletin about the trading intentions (or actual trades) of a well-known figure of the stock market (let us refer to George Soros again as an example) and tries to imitate him. If the trade-based manipulator is capable of attracting a critical mass of investors, then

such a situation can well lead to trend-chasing phenomena, like the ones described above regarding information-based manipulation.

Thus, stock-price manipulation is a practice associated with the realization of trends in the market and as such is a factor affiliated with feedback trading.

2.3.2 Feedback Trading: Empirical Evidence

Empirical research on feedback trading can be classified into two categories, namely “time-series” and “microdata-based”, contingent upon the type of data utilized in each case.

In terms of time-series feedback trading research, one of the most influential papers that has set the pace for relevant research in this area is the one by Sentana and Wadhwani (1992). The authors test for feedback trading on the Dow Jones index using daily data for the 1885-1988 period and document significant positive feedback trading, more so during periods of market declines, a fact which they attribute to the propensity to sell in order to avoid realizing larger losses when the market drops. Koutmos (1997) documents significant levels of positive feedback trading in his study of six developed capital markets for the 1986-1991 period; much like Sentana and Wadhwani (1992), positive feedback trading appears to be rising during market slumps. Using daily data for foreign-exchange markets during the 1987-1997 period, Aguirre and Saidi (1997) failed to come up with any clear feedback trading patterns across a sample of 18 developed and developing markets; actually, the majority of their results indicated that it is negative feedback trading that was found to be present in most cases, a fact they attributed to the prevalence of large “rational” players in currency markets. Koutmos and Saidi (2001) report highly significant positive feedback trading across six Asian

markets during the 1990-1996 period and-again-verify the higher levels of positive feedback trading when the market declines. Watanabe (2002) found significant positive feedback trading towards the TOPIX-index in Japan between 1976 and 1996; his results confirm the previous findings of positive feedback trading rising when the market declines, which he found to be mostly due to margin trading. Bohl and Reitz (2004; 2006) document statistically significant positive feedback trading in the German market on the premises of a variety of indices (C-DAX, DAX30, NEMAX50, NEMAX ALL SHARE) during the 1998-2002 period. Bohl and Siklos (2004) found significant positive feedback trading across both developed as well as developing markets for the 1994-2003 period, while Bohl and Siklos (2005) document higher positive feedback trading levels in the US during market crashes between 1915 and 2004. Finally, Antoniou et al (2005) found that the introduction of index-futures in developed markets has led to a reduction of the impact of positive feedback trading in the underlying spot markets.

Feedback trading research on the premises of microdata dates back to the study by Lakonishok et al (1992) who first estimated feedback trading based upon funds' accounts. Using data on 769 pension funds' accounts in the US for the 1985-1989 period, the authors documented low levels of positive feedback trading, whose significance was mostly concentrated among small stocks. Grinblatt et al (1996) reported significant, yet not particularly large positive feedback trading on behalf of 274 funds in the US during the 1974-1984 period, while Wermers (1999) found higher levels of positive feedback trading among growth-funds in the US during the 1975-1994 period. Jones et al (1999) report highly significant positive feedback trading on behalf of US institutional traders

between 1984 and 1993. Kim and Wei (2002b) documented higher levels of positive feedback trading in the Korean market following the outbreak of the Asian Crisis, irrespective of the type of investor (individual/institutional, indigenous/overseas). Kim and Wei (2002b) produced results indicating that overseas institutional investors in the Korean market around the Asian Crisis did not exhibit uniformity in the significance of their positive feedback trading; offshore funds were found to engage in insignificant trend-chasing compared to their US and UK counterparts. Finally, Voronkova and Bohl (2005) find significant, size-related positive feedback trading on behalf of Polish pension funds during the 1999-2002 period. Finally, Do et al (2006) reported high levels of positive feedback trading among overseas institutional investors in Finland between 1995 and 2004.

Thus, the above findings indicate that positive feedback trading is expected to be more pronounced during periods of declining markets, a fact that must be attributed to the propensity of investors to leave the market as soon as possible so as to minimize their losses. Given however, the leverage of institutional traders in capital markets (Wermers, 1999), this finding may be linked to their aforementioned tendency towards employing positive feedback trading strategies, such as portfolio insurance (Luskin, 1988) in order to protect themselves from realizing large losses during market slumps (an argument that many studies in the field have put forward). Interestingly enough, a number of studies (Lakonishok et al, 1992; Wermers, 1999; Antoniou et al, 2005) find that positive feedback trading need not necessarily be destabilizing and may actually improve market efficiency by accelerating the incorporation of information into securities' prices. Moreover,

the above empirical evidence also seems to indicate that positive feedback trading is significant across capital markets irrespective of their stage of maturity.

2.3.3 Evolutionary Finance and Feedback-effects

Evolutionary Finance has provided us with several examples (Farmer, 2002; Farmer and Joshi, 2002) of feedback-effects in a market, when rational traders interact with their feedback counterparts. The basis of such feedback-effects with possible applications in the field of feedback trading are often models of interactive species, whose coexistence in nature may assume a variety of forms (Edelstein-Keshet, 1987): “*neutralism*” (one species does not affect the population of the other), “*mutualism*” (both populations exhibit a faster simultaneous growth), “*symbiosis*” (one species is necessary for the survival of the other), “*competition*” (two species share a common factor which is in limited supply), “*commensalism*” (one species benefits but not the other), “*amensalism*” (one species suffers from this coexistence) and “*cannibalism*” (when one species, in the absence of the other, resorts to consuming its own members).

We shall now present the model of Lotka-Volterra (1926), which emanates from population ecology and is reflective of a certain type of feedback-based heterogeneity in nature. The Lotka-Volterra model was developed separately by the actuarial scientist Alfred Lotka and the mathematician Vito Volterra (alongside the ecologist Umberto D’Ancona they were studying the ecology of fish in the Adriatic Sea) in the mid-1920s. We feel obliged to note here that the following presentation represents the oversimplified version of the model, which has so far been subject to a rather notable amount of modifications in Economics and Finance.

The Lotka-Volterra model assumes a constrained environment, in which there are only two species, which compete with each other for resources, habitat or territory. The principle of *competitive exclusion* applies here, namely that the strongest prevails, while the weaker is forced to extinction. The “prize” for the most efficient species is a rise in its population ranks. The Lotka-Volterra model can be extended to include more than two species; what follows here constitutes the two-species (simplified, as we mentioned previously) version of the model.

The Lotka-Volterra model was based initially on the following assumptions:

- 1) There are only two populations (species), namely the *Predators* and the *Prey*
- 2) The *Prey* constitute the only source of food for the *Predators*
- 3) The *Prey* enjoys unlimited food supply from nature and face only one threat, i.e. the *Predators*
- 4) *Predators* and *Prey* meet each other in nature, their encounters being random
- 5) Their interactions are *jointly proportional* to their respective population sizes
- 6) There is a single homogeneous ecosystem, e.g. a patch of land

Let P denote the predators' population and V the prey's. Then according to the Lotka-Volterra model, the population growth rate for each is given by:

$$dP/dt = -cP + aPV \quad (1)$$

$$dV/dt = bV - hPV \quad (2)$$

where the constants a , b , c and h are positive.

In equation (1) we note the following: assuming complete absence of prey, the predators' population would decline at a (mortality) rate c . Given the negative effect of the prey's absence upon the predators' population, the sign preceding it is negative as well; hence, $-cP$. As soon as the prey evolve, it is only reasonable to contend that the predators will start encountering them at a higher frequency. How this encountering process will take place is not explicitly denoted; it could be random (individual predators hunting on their own) or not (when predators herd-"collude"-to hunt their prey more efficiently, e.g. to ensure its tracking and capture). Whatever the case, the predators start "attacking" and consuming prey, and this leads to an increase in their numbers. This increase is proportional to the size of both populations and is portrayed here through the constant a .

The " a " has been found to bear different interpretations from those preoccupying themselves with the practical aspect of the model (e.g. population ecology). Sharov (<http://www.gypsymoth.ento.vt.edu/~sharov/PopEcol/popecol.html>) claims that it is the reproduction rate of predators per single prey consumed, Beals (<http://www.tiem.utk.edu/~mbeals/predator-prey.html>) posits that it equals the product of the "attack rate" times the "conversion efficiency" (of food into offspring), with McKelvey (<http://www.stolaf.edu/people/mckelvey/envision.dir/lotka-volt.html>) proposing that it equals the product of the "death rate" of prey per encounter with the predators times the "conversion efficiency". Given the positive impact of " a " over the predators' population, the sign preceding it is positive; hence, $+aPV$.

In equation (2) we note the following: assuming complete absence of predators, the prey' population would rise exponentially at a rate b . Given the positive effect of the predators' absence, the sign preceding it is positive; hence, $+bV$. In the presence of predators, the prey is under attack and their ranks suffer losses pending captivity. The prey's numbers decline at a rate given by the constant " h ", hence the negative sign ($-hPV$). Beals (<http://www.tiem.utk.edu/~mbeals/predator-prey.html>) claims that h should portray the attack rate of the predators we mentioned previously, while Sharov (<http://www.gypsymoth.ento.vt.edu/~sharov/PopEcol/popecol.html>) calls it "predation rate coefficient".

It is interesting to note that the interaction of both populations is assumed to be jointly proportional to their respective sizes; thus, both the increase and the decrease constants (a , h) in the equations are multiplied by PV .

Equations (1) and (2) can also be transformed as follows:

$$(dP/dt)/P = -c + aV \quad (3)$$

$$(dV/dt)/V = b - hP \quad (4)$$

where (3) and (4) provide us with the instantaneous population growth rate for the predators and the prey respectively.

The relationship between the predators and the prey seems to follow a cyclical mode-at least according to the incumbent model. There is a number of prey in the beginning upon which the predators start preying; assuming a constant rise in the prey's population, this preying rate gradually increases. In view of the latter, the predators' population rises (they are able to give birth to new predators) and from

a certain point onwards, this leads to the decline of the prey population's growth. This development is detrimental for the predators' numbers, which are then showing signs of decline as well. Given this, the prey has a chance to recover from the initial offensive and rise again numerically; hence, the cycle starts all over again (oscillation), with the two populations fluctuating together.

We should also stress here that what we have illustrated thus far is the Lotka-Volterra model under the assumption of predatory conduct, i.e. with one species aiming at eliminating the other. Notice also the right-hand side of both equations (1) and (2), where we observe the term PV indicating the encounter rate of the two, which stems from the *law of mass action*; according to the latter, the rate of molecular collisions of two chemical species in a diluted gas or solution is proportional to the product of the two concentrations (see Edelstein-Keshet, 1987).

The Lotka-Volterra model for *competitive conduct*, i.e. for the case where one of the two species does not aim at eliminating the other is based on the Verhulst logistic growth equation. According to this (Edelstein-Keshet, 1987):

$$dx/dt = r x [1 - (x/L)] \tag{5}$$

where r is the exponential growth rate of the population of species x inhabiting a given environment, L is the carrying capacity of that environment (i.e. “the amount of resources expressed in the number of organisms that can be supported by these resources”³) and the $[1 - x/L]$ is the intrinsic growth rate of the population. Hence, in a bi-species setting we have (Edelstein-Keshet, 1987):

³ See Sharov: <http://www.gypsymoth.ento.vt.edu/~sharov/PopEcol/lec5/logist.html>.

$$dP/dt = (C_P)P [(K_P - P - aV) / K_P] \quad (6)$$

$$dV/dt = (C_V)V [(K_V - V - bP) / K_V] \quad (7)$$

where C_P , C_V are the specific (exponential) growth rates of each category of species, K_P , K_V , are the carrying capacities of the environment for each and a (b) represents the population decline caused by the activity of V (P) over P (V).

Population ecology has generated a number of models capable of capturing a variety of interactions in the Lotka-Volterra spirit, apart from the predator-prey; these include host-parasitoid (Thomson, 1922; Nicholson and Bailey, 1935; Rogers, 1972) host-pathogen (Anderson and May, 1980; 1981) models (see Sharov: <http://www.gypsymoth.ento.vt.edu/~sharov/PopEcol/popecol.html>) as well as predator-antipredator models (Sih, 1992).

For more details, see Edelstein-Keshet (1987), as well as the online lecture notes of A. Sharov at (<http://www.gypsymoth.ento.vt.edu/~sharov/PopEcol/popecol.html>).



The presentation of the Lotka-Volterra model in the present context served two purposes. First of all, it provided us with an opportunity to witness how the issue of heterogeneous agents' interaction is pursued in areas outside Finance. Secondly, the predators in the Lotka-Volterra setting are reminiscent of feedback traders, since their conduct is prey-based and as we have already seen, such an interaction gives rise to oscillatory movements of the predator-prey populations. Thus, the Lotka-Volterra model is capable of reflecting phenomena that can be

associated to the Finance-context; this has also been shown through the employment of this model by Solomon (whose extensive work can be found at <http://shum.cc.huji.ac.il/~sorin/my-papers.html>), Farmer (2002) and Sprott (2004). since it has been found to be successful at capturing empirical market non-linearities (e.g. excess volatility). Although Hirshleifer (2001) questioned whether extra-Finance models could be applicable to Finance, our presentation of the Lotka-Volterra model (coupled with the review of the Evolutionary Finance literature previously) reveals that they provide us with useful concepts for further grounding of our Finance research and orientation towards novel directions.

2.4 Herd Behaviour

2.4.1 The Roots: Crowd Behaviour in History

The concept of herd behaviour in the stock market context should not be viewed as a stand-alone case of collective mentality. Historically, herd-instincts have been documented since the early times when humans started to organize themselves in social entities, as the latter facilitated their daily interaction. Before moving on to describing herding in the market context, we consider it appropriate to present the socio-psychological dimension of crowd behaviour. Historically, crowd behaviour has been delineated through the employment of empirical frameworks related to social and political phenomena over time in an attempt to depict the impact of collective psychology upon social dynamics.

Issues related to crowd behaviour are often cited in the Bible: relevant citations can be found in the "Exodus"⁴, "Book of John"⁵, "Book of

⁴ "...Do not follow the crowd in doing wrong"-(Exodus, 23:2).

Matthew”⁶, ”Book of Mark”⁷ and the ”Acts”⁸. Ancient Greek philosophers⁹ tended to regard the crowd as a negative entity that merited avoidance, with the impact of the crowd most excessively felt in ancient Athens, where the demagogues often tried to manipulate public opinion to their benefit¹⁰. Ancient Rome also experienced the impact of the crowd, more so during public ceremonies (Colloiseum) or extreme events (the burning of Rome during Nero’s reign). The mobilizing nature of the crowd was felt in more recent centuries in the undertaking of political movements.¹¹

⁵ “...But this mob that knows nothing of the law—there is a curse on them.”-(John, 7:49)

⁶ “...But the chief priests and the elders persuaded the crowd to ask for Barabbas and to have Jesus executed.”-(Matthew, 27:20)

⁷ “...Wanting to satisfy the crowd, Pilate released Barabbas to them.”-(Mark, 15:15)

⁸ “...they rounded up some bad characters from the marketplace, formed a mob and started a riot in the city. They rushed to Jason's house in search of Paul and Silas in order to bring them out to the crowd.”-(Acts, 17:5)

⁹ Socrates maintained that the solution of every issue should be assigned to the “experts” rather than the “majority” (Plato: “Alkiviades” 135 A). His student, Alkiviades became one of the most interesting figures as a statesman in Athens for being able to play around popular sentiment; his opinion of the latter can be viewed in a relevant dialogue with Pericleus (Plutarchus: “Alkiviades” 7). Alkiviades was under the custody of Pericleus in accordance with his father’s will (Clenius) who was killed in battle (447 B.C.) and was educated by Socrates. Once, when asking to see Pericleus, he was told that this was not possible, as Pericleus was working on a speech in order to give account for certain actions of his before the public in Athens. Having heard that, Alkiviades commented that Pericleus had better consider a way to refrain from giving account to the public. Other philosophers (see, for example, Aristotles (Eudimeia Ethics A, 1214:35), Euripidis (“Orestis” 772-3, “Ekavi” 608) Heracletus (Fragmenta 49) and Plato (Nomoi, Γ, 690:B)) in ancient Athens also shared “eclectic” (i.e. anti-crowd) views, as public opinion in the city was frequently dominated by demagogues; very often, philosophers sharing such views were libelled as “enemies of the people” by demagogues and faced execution. For more on the above, see Natsoulis, T. (1999).

¹⁰ It was commonplace in ancient Athens for demagogues to direct the crowd's anger against their personal opponents with the accusation of anti-democratic conduct. Interestingly enough, those persecuted this way had previously been glorified by the crowd in public for their services to Athens. Examples here include the cases of Alkiviades (Plutarchus: “Alkiviades”), Themistocles (Plutarchus: Themistocles), Kimon (Plutarchus: Kimon) and Miltiades (Herodot: “History”, 6, 136).

¹¹ Le Bon has provided us with a rather eloquent picture of the crowd-behaviour during the French Revolution (1789) as well afterwards in France in his works cited above. Lenin (1902) in his work “What is to be done?” described the means of luring the masses to the objectives of the Communists, using both “Propaganda” and “Agitatie” (Agitation); in brief, the former appealed at the cognitive and the latter at the emotive part of the human psychic. In addition to the above, Lebesis (1941) provides theoretical as well as empirical justification to the formation of what he calls “revolutionary mass”.

Perhaps, the best-known researcher in the field of crowd-behaviour was the French anthropologist G. Le Bon (1895; 1910; 1912) who delved extensively into human behaviour during the post-Revolution political conflicts in France as well as abroad. The main tenets of Le Bon's "crowd theory" were that crowds were of finite temporal duration; they were dominated by the world of emotions; they tended towards extremes; they lacked any sense of collective responsibility; they turned any one of their members from an individual of his own will to an instrument of their deliberations. Le Bon argued in broad lines that the evolution of a crowd is the byproduct of the combination of two sequential forces, namely "suggestion" and "contagion". In rough terms, the former pertains to the exposure of an individual towards a given belief, while the latter refers to the active alignment of the individual's behaviour to the behaviour suggested by that belief. The success of "suggestion" here is a function of the belief's vagueness; the vaguer it is, the more subject it can become to various interpretations by different people. Simply put, it constitutes a belief of clear presence and unclear detail and it is the latter that impedes rational thinking (information surrounding it is incomplete) with the potential of driving people into action towards a certain direction. At this point, "contagion" comes into play; the more people subscribe to this idea, the more intense becomes the "social pressure" towards others to follow it, either "passively" (through the sidelining of objections) or "actively" (through agitation, i.e. active participation in the spirit of the idea).

Le Bon's theories may be viewed as out-of-date as they refer to sociopolitical structures dating well over a century ago. Indeed, most of Le Bon's works date back to the end of the 19th century and the beginning of the 20th. However, the strength of Le Bon's theories stems from the fact that they are

empirical in nature, i.e. they are based upon the observation of behaviours and events and is not the byproduct of some abstract thinking. It is interesting to note that many researchers in Finance include Le Bon in their studies of herd behaviour (De Bondt and Teh, 1997; Lynch, 2000).

Thus, the issue of herd behaviour in the market-context traces its roots deep in the historical evolution of human societies and goes, as we shall shortly describe, hand in hand with the psychology of the human being.

2.4.2 Herd Behaviour in the Stock Market: Definitions, Sources and Motivations

Let us now go back to the concept of investors' interaction. If heterogeneous traders were present in the market, then we would expect them to normally diverge in their trading patterns given the aforementioned complexity. It might be the case, however, that despite their heterogeneity, it is convergence that finally prevails. How this convergence is attained is a rather thorny issue, which also is not subject to one-sided explanations; one interpretation that has been put forward in the literature is related to herd behaviour.

Any theorizing with respect to herd behaviour is bound to stumble upon popular beliefs¹² relative to the issue; herd instincts have often been cited as the impetus underlying abnormally volatile market returns (Kindleberger, 1978; Galbraith, 1994), the latter being reminiscent of Keynes' remarks about "animal instincts" in the stock market (Keynes, 1936). Popular beliefs aside, however, we

¹² James Dines (author of "How Investors can Make Money Using Mass Psychology") argued on CNN Money about investors' wolfpack-sentiment when dealing with evolving trends in the market. Kenneth Chang (ABC News) also spoke of trend-chasing mentalities in the market based upon the research by Lux and Marchesi (1999).

shall try to focus on the academic debate on the topic; to that extent, we will try to pursue a conceptually clear line of argument so as to mitigate against potential misunderstandings.

Herd behavior requires *participation*, by definition. Herds are not formed abstractly; they presuppose the presence of individuals who behave in a way that promotes the cohesion of the herd. Whether herds form by themselves or through external influences is a question with rather far-reaching implications. Indeed, the line between the two might be difficult to discern, more so, since this would directly involve policy implications. For the moment, suffice to say that herds are based on the participation of individuals, more specifically investors, in the case of stock markets.

The stock market, as of itself, constitutes a mechanism that encourages social participation through the provision of the opportunity of realizing higher expected returns. Whether this proves to be the case or not is another matter; one need only add here that people tend to invest in securities in anticipation of future gains that could not easily have been realized through other types of investment of less risky nature (e.g. government bonds). Therefore, it would perhaps be reasonable enough to claim that the stock market appeals to the “*economic motive*” of the human psychic.

Investors, much like, every human being, do not live in isolation; on the contrary, they dwell in societies among other people with whom they interact. The mode of their interactions may manifest itself in various ways; however, it always assumes a common denominator: *observation*. It may be that people like what they observe, i.e. they experience an agreement with it and it may be that they do

not. If they agree with the course of action suggested by the observation, they may choose to follow it, whilst if they disagree with it they may choose to abstain from it or choose an alternative route. In the former case one might speak of “*convergence*”, while in the latter of “*divergence*” (of actions or opinions).

Therefore, convergence of opinions combined with convergence in trades following interactive conditions lead to what is known as herd behavior. Hirshleifer and Teoh (2003) have defined herding as a “behavioural similarity” stemming from the interactive observations of individuals. In the stock market context, one might be bold enough as to classify these observations into two categories, namely *Actions* and *Payoffs*. Hence, people observe/hear/read about the stock selection of other people or, what is more they may also get to find out about the outcome of such selections (whether somebody made a profit or a loss). In strict terms, it is this interactive process among investors that generates herding; therefore, herding in a strict sense cannot exist in the absence of interactive observation.

In the presence of herding, we expect to notice investors’ trades to converge as we just said. Convergence, though, is not uniform across time; indeed, we do not expect herding to materialize *ad infinitum*. The reason is that those willing to participate in the herd, as this is perceived, are not infinite in numbers. Hence, their ranks may not offer the respective demand-size necessary for the price-ascension and sustainability of its underlying trend; alternatively, adverse circumstances may lead part of their dynamics not to be realized (e.g. an economic downturn might deter those who would otherwise trade from doing so). What is more, a herd can materialize in any stock, industry or market: hence, herds do not exhibit preferential patterns.

Herding may involve *intent* (*intentional herding*) or it may not (*spurious herding*); this categorization plays a quintessential role in the deciphering of its presence in the market context (Bikhchandani and Sharma, 2001).

The case for intentional herding is a rather complicated one; what it posits is that people consciously follow each other's trades. In short, their trades converge due to the influence of *imitation*. Under such circumstances, we expect investors to discard their private information and use the actions (trades) of their peers as informative signals. However, the notion of intent here is quite problematic. Intent *per se* is an abstract term and as such is hard to enumerate or quantify. A stock market accommodates millions of investors and it is obviously impossible to control for each one's intent at any point in time. This issue has also been at the forefront of specific issues in economics (see Utton, 1995), namely those dealing with collusion and predatory pricing and we shall attempt to briefly describe the underlying rationale there so as to understand the impossibility of the establishment of intent in finance.

Collusion pertains to the specific business conduct followed by firms when they operate in concert and can be distinguished into tacit and explicit. Explicit collusion is the case of the cartels: an oral or written agreement binds all firms in a market towards cooperative behaviour; cartels normally appear in markets where the number of firms is small (oligopolies). Tacit collusion occurs when there are a few firms in a market, with each one monitoring each other's pricing policy and adjusting their respective prices accordingly. This is also known as "parallel pricing" and may provide the impression that some connivance is at work. The fact that both forms of collusion may materialize in markets with high levels of concentration renders their distinction often problematic. As the US antitrust

legislation proposes, a price-plus approach is to be employed when the issue is surrounded by substantial ambiguity; price-plus here implies that intent, other than collusive pricing alone, must also be established.

Similar considerations apply to *predatory pricing*, namely the pricing adopted by a firm with the intention of eliminating incumbent competitors and deterring potential ones from entering. However, if a firm is technologically advanced, it may reach levels of efficiency that allow it to place a very low price for its products, i.e. engage in competitive pricing. Again here, the US antitrust framework calls for the investigation of intent in order to decide upon the imposition of penalties or not, without restricting itself to the establishment of predatory pricing *per se*.

However, intent in such cases is obviously a matter of subjective content and refers to the discretion of the relevant authorities to decide whether it actually exists or not. If that is the case with well-defined targets (a limited number of corporations), then it is apparently impossible to assert the presence of intent in the ranks of a population of millions of investors, indigenous and overseas.

What's more, the case for intent seems to be of interest in economics due to its policy implications. If a company practices predatory pricing, then this obviously merits regulatory intervention to prevent competition from being curtailed; similar considerations apply in the case of collusion. However, financial regulation would probably not preoccupy itself with the existence or not of intent in investors' decision-making. After all, intent is a private issue that may or may not be associated with an individual's background as well as other factors. Indeed, it could not be considered as reasonable-let alone feasible-to accuse an individual investor for trading according to a specific pattern intentionally. Intent is taken

into account when the outcome of the market is compromised or influenced, such as in the case of manipulation, not when an investor trades on the basis of a conjectural cognitive bias. Hence, the matter of intent in the herding literature falls more into the sphere of theoretical intuition rather than practical application.

Rationalizing imitation is thus, not always possible. It is worth, however, trying to provide some explanations related to its motives. First of all, one should refer to the *conformity bias*, namely the condition under which people feel more convenient when doing what others do. This tendency towards conformity (Hirshleifer, 2001) may well be related to the interaction of people, as they communicate with one another. Communication may be explicit (e.g. when people are conversing - see Shiller, 1995), yet it may also be tacit (when people observe others' choices, e.g. in fashion – see Bikhchandani et al, 1992). One might also ascribe this propensity towards imitation to certain behavioural biases, such as the *representativeness heuristic*, *limited attention*, the *false consensus effect*, the *curse of knowledge* and the *home bias*, in line with the discussion in Hirshleifer (2001) and Hirshleifer and Teoh (2003).

However, copying the decisions of others may well be the result of other, more subtle, considerations. A trader who possesses no private information or perceives others as better-informed may choose to free-ride on the informational content of others' actions, thus resolving his informational handicap. Similarly, a trader who maintains an inadequate capacity for information processing may also be prompted to follow his peers, if he considers their relevant capacity superior to his. Assuming the prevalence of such considerations, it is perhaps reasonable to contend that these are bound to lead to negative informational externalities. If traders mimic each other and do not trade on the basis of their own information,

then the latter will not be revealed and incorporated in the public information pool, thus leading that pool to grow poorer. This may lead to temporary blockages of information or to its slower aggregation (see the discussion in Hirshleifer and Teoh (2003) for more theoretical grounding on the subject). Thus, the anticipation of *payoff externalities* in terms of information may constitute a valid justification in favour of intentional herding (Devenow and Welch, 1996).

A relevant case here involves *informational cascades*, where market participants may ignore their private information and follow the actions of others, when they consider the information conveyed by others' actions to provide a useful set of information on its own (Banerjee, 1992; Bikhchandani et al, 1992). If so this is also expected to lead to a poorer aggregation of information in the marketplace, as the private information of "cascading" investors is not revealed to others (since it is suppressed). This is expected to be particularly strong in cases where the available options to follow are limited, since, if the latter holds, the behavioural responses possible will be limited as well, thus enhancing the potential for converging to one of them (Devenow and Welch, 1996).

However, investors may decide to imitate others based upon more material considerations. A series of studies (see Hirshleifer and Teoh, 2003 for a review) claims that investment professionals (e.g. fund managers) may in fact engage in herding among themselves due to *professional* reasons. Career-related concerns seem to constitute an interesting area of research when it comes to assessing the impact of managers' herd behavior. The basic question here relates to agency problems as fund managers are essentially in the employment of investment companies and, as such, are subject to principal-agent considerations. As their performance is evaluated periodically on a relative basis, i.e. versus the

performance of their peers, mostly those with similar (e.g. stocks, bonds, money-market, industry, foreign market/s et al) specializations (Ross et al, 1999), this creates a perceived “benchmark” upon which they may attempt to herd.

Since some investment professionals may be more able (let them be denoted as “good”) and others less able (“bad”, hereafter), the issue of their relative performance evaluation can turn into a predicament as Scharfstein and Stein (1990) show. In their study, the evaluation of the professionals’ ability on a relative basis is bound to render imitation tempting, if this is going to induce “jamming” to the evaluation-process. “Bad” (i.e. less able) managers have an obvious incentive to copy the actions of their “good” (more able) peers, if this will help them appear as “better” professionals. “Good” managers, on the other hand, may choose to follow the investment-decisions of the majority of their peers, even if these are sub-optimal; this may be the case, if the risk from a potential failure is perceived as higher compared to the benefits accruing from a potential success by “going-it-alone”. Thus, the issue of separating “luck from skill”, namely telling the “good” managers from the “bad” ones, as Lakonishok et al (1992) argue, becomes harder to establish in this context.

Here is how the “jamming” might work. Assuming that positive circumstances materialize in the market, then from a conformity point of view every manager would like to perform well, as a potential negative performance might cast a stigma over his perceived ability. Also, if everyone performs well in a euphoric market, a negative performance is not desirable as it makes a manager “stand out from the crowd”. Thus, “bad” professionals will presumably be inclined to “herd” on the actions of their “good” peers, so that everyone gives the impression of being “good”. Conversely, if adverse circumstances materialize, it

is hard to tell who is good (the “bad” ones will have performed bad anyway, while the “good” ones will have probably performed worse than expected). It follows that fund managers have an incentive to herd in both cases.

Reputational considerations are relevant to the aforementioned agency-concerns, as they may also encourage fund managers to herd. A professional who enjoys a strong reputation in his capacity has an incentive to imitate others in order to preserve his reputation (Graham, 1999); this can be the case if the damage to his reputation by a potential failure outweighs the expected benefits from a potential success. If we assume that the well-reputed professionals are also the better-able ones (as it is hard to imagine how one’s reputation would have grown in the absence of a distinctive ability), this may help explain the herding tendencies denoted previously with regards to the issue of ability. Managers with a weak reputation, however, may also resort to herding as a means of free-riding (Trueman, 1994) on the reputation of better-reputed colleagues (*reputational externality*).

Another factor that may tacitly promote herding instincts among investment professionals (be they fund managers or financial analysts) is *relative homogeneity*. Investment professionals constitute a group of more or less similar traits: they share a similar educational background, are exposed to similar information signals, may tend towards interpreting them similarly (due to background-similarities or peer-mimicking) and are subject to a similar framework of professional conduct (e.g. compensation schemes, notions of prudence and fiduciary duty (De Bondt and Teh, 1997). If so, fund managers may tend to exhibit similarities in their trading conduct, by maintaining, for example, similar structures of their portfolio-holdings (the case of fund managers selecting

stocks picked up by many of their peers-see Lakonishok et al, 1992) or adhering to the line of the “opinion leaders” or the perceived majority (as may well be the case with financial analysts-see, e.g. Graham, 1999 and Welch, 2000).

Market manipulation may also promote herding, as the actions of a group of informed traders may create the impression of a profitable opportunity, thus luring others into it (Van Bommel, 2003). The mechanism involved in such cases may well lead to the manifestation of herding phenomena, as Mathiopoulos (2000) for example, has described and can also be associated with positive feedback trading, where individuals engage in trend-chasing induced by rational speculators (De Long et al, 1990; Andergassen, 2003).

Contrary to intentional herding, “*spurious*” *herding* seems to be more complicated in nature. What it essentially posits is that investors trade to the same direction for reasons other than imitation. Spurious herding involves a similarity in responses to similar decision problems following commonly observed signals (Bikhchandani and Sharma, 2001) and needs to be distinguished from the expressions of “intentional” herding depicted thus far. If a change in fundamentals (e.g. a drop in deposit rates) materializes, this may well have the potential of inducing investors to behave in a parallel fashion (e.g. possibly invest more in stocks). However, as everything is relative in research, even this needs to be viewed with skepticism: indeed, some traders may intentionally follow others in this case, if they feel unable to appropriately decipher the content of the signal that has arrived at the market, or if they just feel like trading to the same direction as others do.

Nevertheless, this type of “unintentional” herding may be mistaken for intentional, a fact that has also been ascribed by Hirshleifer and Teoh (2003) to

the *Simultaneous Causation Issue*. The latter refers to the fallacy of misperceived herding due to conceptual errors. Herding, as we have just noted, requires interactive observation between traders. However, it might be the case that traders may behave in a herd-like fashion in the absence of interactive imitation. This might be true when something causes their trades to converge or when they respond in a rational manner to price movements; the next example might be enlightening in this respect.

If group A is herding towards a stock, then group B may find it convenient to follow suit in order to exploit group A (or its trades), thus engaging in what one might term as rational speculation. The paper by De Long et al (1990) is particularly relevant here as the authors show how rational traders may choose to herd alongside a trend they have originally fostered and speculate on the purportedly uninformed positive feedback traders who will be lured into it. Here this comes very close to spurious herding, although herding is not explicitly mentioned throughout the paper. Spurious herding involves correlated trades and presupposes no interaction among traders (and, of course, no intent). Thus, in this case, a confluent rational response to a given price course could be deemed as herding.

The issues arising from herding have obvious implications for *market efficiency*. As herd behaviour postulates, people's trades need not be motivated by information; investors may simply lack any information (or perhaps, more plausibly, the information necessary to decide upon whether to invest or not) or may hesitate to trade on the basis of their private information for a variety of reasons (due to difficulty in its processing or due to its bad quality). If so, then

investors may trade on the basis of others' trades, a situation at odds with the tenets of market efficiency.

However, this is not the sole consideration here, as information- or non-information-based trading is only one issue; securities' pricing is another. Let us suppose for the sake of the argument, that information arrives at time t and that "rational" investors trade according to it. All else equal, one might expect prices to rapidly incorporate this information and adjust at the "efficient" levels; this would, though, constitute only one presumption. If a number of traders decide to condition their trades upon the trades of others, it might be reasonable to assume that the adjustment of prices to new information at time t might be viewed as the beginning of a given trend, however erroneous a perception of the kind might be. If the information is positive and (as expected) prices rise to reflect this good news, then it is possible that a set of traders might choose to buy that stock not in response to good news only but also in response to the response of others to it. Essentially, this is tantamount to what we mentioned previously about Soros' (1987) market "reflexivity". Although beyond the scope of our analysis, we may perhaps safely assume that a behaviour as such has the potential to generate price overreaction. Although rational arbitrageurs might be ready to counter this mispricing, the possible amplification of noise-traders' risk (Barberis and Thaler, 2002) may render arbitrage a less attractive option.

Of course somebody might argue that market efficiency may still apply in this case as the following example shows. Let us assume that a large trader invests in a stock for some reason and that this investment of his is advertised in the press. A rather possible outcome of this publicity is that his trades constitute now part of the public information pool that other traders can observe and may choose

to follow. The question here is whether trading on others investors' trades is in line with "rational" behaviour. In our opinion, no answer can be provided here without running the risk of arbitrary judgement. If we were, however, to cast aside issues of malevolent nature (namely that the "big" trader may be trying to lure smaller ones only to profit from them at a later stage), we might say that a situation like this does not necessarily compromise market efficiency. As long as prices reflect all information available, investing on the basis of information regarding the trades of others seems to be quite in line with the EMH. Of course whether this conditioning of trades is intentional (following a large trader due to imitation) or spurious (similarity of responses due to commonly observed signals, albeit with a time lag) remains yet to be established.

2.4.3 Herding: Empirical Evidence

Research on herd behaviour, much like the one on feedback trading, has resorted to the employment of both aggregate data (i.e. returns) as well as microdata (i.e. investors' accounts) in order to estimate herding.

The return-based herding literature has taken herding to be reflected into the cross-sectional dispersion of returns from the market average, the assumption being that a rise in herding would be imprinted into a decline of that dispersion, as returns would tend to conform to the market's perceived consensus. The seminal paper in this area was the one by Christie and Huang (1995) who used daily (1962-1988) as well as monthly (1925-1988) data for the US market in order to test for herding at the industry-level during periods of market stress. The latter related to "extreme" returns, which were defined as lying two or three standard

deviations from the period's market-mean. Using a linear model framework, Christie and Huang (1995) documented the absence of herd behaviour in all industries tested, as the cross-sectional dispersion of stocks was found to be increasing irrespective of the "extreme" returns being positive or negative. Interestingly enough, the increase in dispersion was found to be more during "extreme up" versus "extreme down" market periods, indicating perhaps a greater uniformity of returns' dispersion during the latter.

Chang et al (2000) modified the Christie and Huang (1995) model to incorporate the possibility of nonlinearities in the market as well as directional asymmetry, i.e. differing responses of herding in up- versus down-markets. Their results involved both developed (US, Hong Kong, Japan) as well as developing (South Korea, Taiwan) markets, with the presence of herding established, significantly so in the latter. Much like Christie and Huang (1995), their findings also indicated a higher rate of increase in the cross-sectional returns' dispersion during up- compared to down-markets for all markets examined.

Using data on thirteen commodity futures contracts traded on three European exchanges (London Futures and Options Exchange; International French Futures and Options Exchange; Agricultural Futures Market Amsterdam), Gleason et al (2003) documented the absence of herding during the 1990s (futures contracts of different commodities were tested for different subperiods) on the premises of the Christie and Huang (1995) model; contrary to Christie and Huang (1995) and Chang et al (2000), the cross-sectional dispersion of returns was found to be more uniform during "extreme up" periods as opposed to "extreme down" ones.

Gleason et al (2004) utilized a unique database of tick data for Exchange Traded Funds on the AMEX for the 1999-2002 period and, using the Christie and Huang (1995) and the Chang et al (2000) measures as well as a hybrid of the two, they documented the absence of herding during extreme markets movements. Again here, their findings also indicated a higher rate of increase in the cross-sectional returns' dispersion during "extreme up"- versus "extreme down"-markets.

Hwang and Salmon (2004) tested for herding on the basis of the cross-sectional dispersion of the factor-sensitivity of assets. According to their theory, when investors are influenced by behavioural biases, their perceptions of the risk-return relationship of assets may be distorted. In the presence of herding towards the market consensus, it is possible that the betas of the stocks will deviate from their equilibrium values. Thus, the beta of a stock does not remain constant (as the conventional CAPM would posit), but changes with the fluctuations of investors' sentiment. As a result, the cross-sectional dispersion of the stocks' betas would also be expected to be smaller, i.e. the stocks' betas would tend towards the value of the market beta, namely unity. Their findings indicated the presence of significant herding in the US and South Korea during the 1993-2002 period, more so outside turbulent periods.

Caparelli et al (2004) tested for herding on the premises of the COMIT-index in Italy using the methodologies of Christie and Huang (1995), Chang et al (2000) and Hwang and Salmon (2004), although the results generated were mixed. Finally Demirer and Kutan (2006) tested for herding in the Shanghai and Shenzhen markets between 1993 (1994 for Shenzhen) and 2001 using the Christie and Huang (1995) model and reported insignificant herding; in line with Christie

and Huang (1995), Chang et al (2000) and Gleason et al (2004), the cross-sectional returns' dispersion during "extreme up"-markets was higher compared to "extreme down"-markets.

The empirical tests for herding using microdata date back to the seminal paper by Lakonishok et al (1992), which set the pace for research in this area. Lakonishok et al (1992) found insignificant herding among pension funds in the US during the 1985-1989 period, a finding corroborated also by Grinblatt et al (1996) for US mutual funds between 1974 and 1984. However, Lakonishok et al (1992) also produced results indicative of an inverse relationship between fund-herding and stock-size; thus, funds herded more in smaller capitalization stocks. Similar results with regards to the size-effect were reported by Oehler (1998) for German mutual funds during the 1988-1993 period and Wermers (1999) for US-funds during the 1975-1994 period; actually, Wermers (1999) reported that the propensity towards herding was found to be higher among growth-oriented funds.

South Korea is a market that has been extensively investigated for herding, more so in the aftermath of the Asian Crisis and the related impression of overseas investors being the culprits for the latter. Choe et al (1999) showed that foreign funds herded less during the Asian Crisis compared to the period before it, while Kim and Wei (2002b) found that herding on behalf of various investor-types (individual-institutional, indigenous-overseas) was higher following the outbreak of that Crisis. Kim and Wei (2002a) found that offshore funds herded less compared to their other foreign institutional counterparts around the Asian Crisis.

Further results indicative of significant institutional herding were documented by Jones et al (1999) for US institutional investors during the 1984-1993 period, Gilmour and Smit (2002) for South African unit trusts between 1991

and 1999, Olivares (2005) for Chilean pension funds during the 1997-2001 period, Voronkova and Bohl (2005) for Polish pension funds during the 1999-2002 period and Lobao and Serra for Portuguese equity funds between 1998 and 2000. Wylie (2005) documented insignificant herding for UK funds between 1986 and 1993. Finally, Do et al (2006) found high herding levels in Finland among investors, most notably individual ones, between 1995 and 2004.

Thus, as empirical evidence appears to indicate, herding exists in both emerging and developed markets and can be found to be significant in the behaviour of market participants, irrespective of their classification.

Return-based herding models seem to point towards the absence of herding during extreme market periods, thus implying that turbulent periods discourage herding, perhaps due to the lack of a definitive market direction, as Hwang and Salmon (2004) postulate.

Microdata-based models furnish us with results indicative of existing herding tendencies on behalf of institutional investors, more so in emerging capital markets. What is more, institutional herding seems to increase as the stock-size declines, thus indicating a possible size-effect in the herding of mutual funds. Such findings regarding institutional herding (higher in emerging markets / small capitalization stocks) could be related to informational reasons. Both emerging markets as well as small-capitalization stocks are normally characterized by ambiguous informational environments. Emerging markets are expected to be more prone to informational inefficiencies (Antoniou et al, 1997a) due to the incompleteness of the relevant regulatory framework reining their operations. Small stocks, on the other hand, tend to enjoy limited analysts' coverage (Hirshleifer, 2001), while the information pertaining to them is usually firm-

specific and more difficult to substantiate. In the presence of such informational uncertainty, it may be reasonable for fund managers to opt for following their peers instead of going-it-alone.

2.5 Conclusion

In this chapter we have delineated the two main schools of thought in Asset Pricing, namely the Rational one as imprinted through the Efficient Markets' Hypothesis (Fama, 1970; 1991) and the Behavioural one, as reflected through the advances in the employment of psychology into Finance (Barberis and Thaler, 2002). We documented the significant increase of research in the area of heterogeneous-agents' modelling on the premises of Behavioural Finance and discussed the expansion of such research in novel areas, most notably those of Evolutionary Finance. The heterogeneity of market agents, in turn, can be translated into the manifestation of a multitude of strategies, which is expected to further enhance the complexity of the market. Given that markets are subject to evolutionary dynamics, their structures are not expected to remain stationary over time. This implies that the manifestation of the various trading strategies in the marketplace is bound to be influenced by the changes in the latter. However, it is interesting to note that the impact of differential market features and conditions upon the manifestation of trading strategies has received rather scant attention in Finance.

We assumed the behavioural patterns of *herding* and *feedback trading*, whose properties have constituted the subject of voluminous research, both analytical as well as empirical in Finance, in order to study the impact of differential market

features and conditions upon their behaviour. These two patterns of trade constitute rather popular topics in Finance research, more so given their treatment by popular Finance literature as culprits regarding market abnormalities (Soros, 1987; Galbraith, 1994; Mathiopoulos, 2000).

Regarding feedback trading, our research delved into both analytical as well as empirical work in the field. We noticed that feedback trading has been taken to be a proxy-pattern for noise trading, since, as we mentioned previously, it is impossible to designate a uniform noise-trading pattern. Using this as a stepping stone, a variety of analytical and empirical papers has tried to picture the significance and impact of feedback traders through model-settings where noise traders interact with fundamentals-driven investors. However, the above settings tend to overlook two issues. Firstly, rational investors may themselves choose to employ feedback-style trading rules as well, as has been implied both in analytical (De Long et al, 1990; Farmer, 2002; Farmer and Joshi, 2002; Andergassen, 2003) as well as empirical works (Soros, 1987; Luskin, 1988; Antoniou et al, 2005); therefore, feedback trading, irrespective of its expression, need not solely be confined to noise traders. Secondly, the bi-trader setting (rational versus feedback traders) in most relevant models appears to constitute a rather restrictive reflection of investors' heterogeneity in the marketplace. Finally, as has frequently been noted thus far, absent the aforementioned study by Antoniou et al (2005), there has been no other research on the impact of market factors upon feedback trading. To that end, we decided to conduct our research on the premises of feedback trading based upon two pillars, an analytical and an empirical one.

The analytical pillar relates to the utilization of the “rational-feedback” model proposed by Sentana and Wadhwani (1992) and its extension through the insertion of a third trader-type, reflective of a novel trading pattern, into it. The sole purpose of this novel trader-type is to exploit feedback traders by taking advantage of the basis (and potential byproduct) of their trading conduct, i.e. the trend through the implementation of a specific strategy. The latter, as we shall illustrate in Chapter 3, involves *engaging in feedback trading whenever a specific indicator produces a signal implying that it is beneficial for him to trade*. Thus, this novel strategy is not “rational” in its strict sense (since it involves feedback trading), yet it also cannot be considered “uninformed”, since it is based upon some information; such modes of “non-fundamental” speculation have been documented in a small number of analytical papers (see e.g. Allen and Gale, 1992; Madrigal, 1996), yet empirical work on the subject has never been carried out. Consequently, this novel trader-type of ours contributes to existing literature on heterogeneous agents, in general and feedback trading, in particular in two distinctive ways: first, by introducing and empirically testing for an novel feedback trading pattern and secondly by increasing the heterogeneity in an existing heterogeneous-agents’ model through the inclusion of this trader-type into the latter.

The second pillar engulfs the *empirical* component. As this novel trader-type is added to an existing bi-trader model-framework, it enhances the heterogeneity of the latter. As a result, it would be interesting to see whether its presence exhibits differences in its significance across market environments characterized by varying levels of investors’ heterogeneity. We test for this using a sample of markets with different levels of heterogeneity, the latter proxied through the

participation levels of various investor-types. We consider the degree of heterogeneity of a market being an increasing function of the participation levels of overseas traders, since the trades of foreigners are often subject to regulatory restrictions. As a result, the more *restrictive* the market environment is, the more barriers to trade foreigners are expected to face and the more reduced their participation levels will be, thus limiting the market's heterogeneity. Conversely, the less restrictions a market has in place, the easier it is for overseas investors to trade, thus boosting their trading levels and, concurrently, the heterogeneity of the market. *The idea underlying our intuition here is that the less restrictive a regulatory environment is, the more participation it will attract by various categories of investors, thus expected to allow for the manifestation of a greater array of trading strategies.* As a result, our novel type of trader would be expected to manifest itself more clearly in liberal market environments. Given that regulatory frameworks are subject to change, thus inducing changes in the heterogeneity of the market, the impact of those changes upon our proposed trader-type is examined across time; finally, we investigate whether this trader-type exhibits differences in its presence and significance during turbulent versus non-turbulent market conditions.

As a result, the above investigation of feedback trading is conducted upon an *ad hoc* developed analytical framework aiming at addressing the issue of *whether specific market factors* (market heterogeneity, extreme versus non-extreme market conditions) *impact upon the significance of feedback trading* across different markets.

Regarding herding, it constitutes a concept that has been studied extensively, as the reviews of Bikhchandani and Sharma (2001) and Hirshleifer and Teoh

(2003) illustrate, on an analytical basis (i.e. through models that attempt to picture various possible theoretical manifestations of it), as well as on an empirical one (using both aggregate¹³ as well as proprietary¹⁴ data). Our research has indicated that, much like with feedback trading, there appears to be rather limited attention towards the impact of specific market-features and conditions upon herding, both at the single- as well as the inter-market level (i.e. across markets).

To that end, we tested for herding across various markets in Chapter 4 on the basis of several regulatory features (capital gains' taxes, short-selling constraints and index-futures' introduction) which are capable of affecting herding. Our intention here was to address the research issue of *whether the presence or the absence of those features promoted or inhibited the significance of herding*. To the best of our knowledge, this is the first research attempting to study herding on the basis of specific, herd-related market-features, in general and the aforementioned features, in particular. In view of the popular belief regarding the destabilizing potential of herding, we contend that the issues investigated here provide novel insights into features that may facilitate herding from a regulatory point of view, thus being of interest to the relevant authorities.

Given the leverage of mutual funds in capital markets (Wermers, 1999) and the potential for destabilization-inducing herding on their behalf (Kim and Wei, 2002b), we devoted Chapter 5 to the study of institutional herding. Using a unique database of institutional traders' holdings, *we investigated the presence and significance of institutional herding exclusively at the level of the constituents of a market's index on the premises of specific features of that index reflective of*

¹³ Mostly stock returns.

¹⁴ Such as investors' accounts and transaction data.

market conditions that have the potential of bearing an impact upon herding; these features included market-wide herding, trading volume, market volatility and market direction. Again here, the main issue examined is *whether these herd-related conditions are capable of conferring an impact upon institutional herding.* Our exploration of the herding literature has indicated that an examination of herding, in general and institutional herding, in particular has never been undertaken before on the basis of such a framework. Researching institutional herding in this fashion raises issues of interest to regulators (if specific market conditions do impact upon institutional herding, then they may decide to curb such tendencies through the initiation of anti-herd incentives) as well as the wider investment community (since certain derivatives are based upon market indices- e.g. index futures).

Consequently, the investigation carried out in our research contributes to the Finance literature in several distinctive ways. First of all, we link two behavioural patterns of investors' heterogeneity with the underlying market environment in an effort to demonstrate the impact of specific features and conditions of the latter over those patterns over time both in a single market (Chapter 5) as well as across markets (Chapters 3 and 4). Our work contributes to the theoretical debate on those behavioural issues both at the *analytical* level (by devising *ad hoc* model-settings: Chapter 3) and the empirical one (by examining those patterns on the basis of their relationship with specific market features and conditions; Chapters 3, 4 and 5).

Chapter 3

Threshold-trading: A Theoretical and Empirical Investigation of a Novel Type of Feedback-trading

3.1 Introduction

Research in Finance has tended to portray market heterogeneity in the context of information-asymmetry, where market agents differ both with respect to the possession as well as the processing of information. Traditional market microstructure literature (see O' Hara, 1997 for a detailed thematic overview) distinguishes often between traders who have access to information ("informed") and traders who have no access to information ("uninformed") and trade for reasons other than information (e.g. liquidity). Other researchers (see e.g. De Long et al, 1990; Farmer, 2002; Farmer and Joshi, 2002; Andergassen, 2003) assume that informed rational speculators take advantage of their informational superiority *ad hoc*, i.e. in order to exploit the deviations of prices from fundamentals arising from the behavioral trading patterns of their "noise" counterparts.

However, assuming that some traders are enjoying a superior informational position while the rest are trading on "noise" is probably an inaccurate reflection

of investors' "biodiversity" in the marketplace. A series of papers (Allen and Gale, 1992; Madrigal, 1996; Mei et al, 2004; Hamadi et al, 2005) have explored the possibility of uninformed investors' exploitation by traders who do not necessarily subscribe to the rational paradigm. These models purport that there are investors who might choose to exploit noise traders through some specific information pertaining to their trading conduct without any explicit knowledge/employment of fundamentals.

To exploit noise traders' behaviour in such a way, however, it is necessary to specify their trading pattern. Given that "noise" itself is hard to elaborate, a number of heterogeneous-agents' studies have resorted to the association of noise trading with feedback trading (i.e. trading on the basis of past prices).

Feedback traders *per se* are not necessarily uninformed or irrational (Antoniou et al, 2005); however, trading on past prices can lead to perceptions of "price-trending". If so, feedback traders can have an impact on price-behaviour, in the sense that they may lead to the launch of a new trend or the exacerbation of an existing one. A reasonable assumption here is that, one way to exploit feedback traders is to exploit the basis (and potential byproduct) of their trading conduct, i.e. the trend.

We explore the possibility of such non-fundamental, noise-exploiting behaviour by introducing a novel trader-type, whose purpose is to exploit the trend by implementing a specific strategy. The latter, as we shall later illustrate, involves trading on the trend following the violation of a certain threshold, hence we will be referring to this trader-type as "threshold trader". This is tantamount to saying that this investor trades on the trend whenever (according to his specific strategy) it is beneficial for him to do so. Although this trader-type does not

conform to the traditional rational, “fundamentalist” type, his trading pattern is founded upon the utilization of a specific informational signal (reflected through the violation of a threshold). As a result, he cannot be termed “uninformed” in the strict sense, since he is utilizing some information, albeit non-fundamental.

A key distinguishing feature of our research relates to the empirical testing of the presence of this novel trader-type. As the research on non-fundamental trading/speculation has mostly involved analytical modeling, we considered it appropriate to test whether the existence of a trading conduct of the sort can be controlled for, by using real market-data. As a result, we do not only devise a hypothetical trader-type, but we also test for its presence empirically, across a number of capital markets. Our purpose is to study the “threshold” trader-type within different regulatory environments, in order to examine whether its presence is influenced by a market’s heterogeneity. To proxy for the latter, we use data on the decomposition of a market’s turnover by investor-type and consider the participation-levels of overseas traders as indicative of the degree of the market’s heterogeneity. Since foreign traders are subject to differential treatment across markets contingent upon the degree of financial liberalization of each, the more “liberal” a market is, the higher the participation of foreigners is expected to be.

The rest of the chapter is organized as follows: Section 3.2 includes a review of the literature pertaining to heterogeneous-agents’ models relative to noise-traders’ exploitation. Section 3.3 presents the entire model-development of our concept, Section 3.4 delineates the hypotheses relative to this novel trader-type, while Section 3.5 offers an overview of the markets for which these hypotheses are tested (always within the context of our hypotheses). Section 3.6 discusses the methodology employed (3.6.1), the data utilized (3.6.2) and presents some

descriptive statistics (3.6.3). Section 3.7 presents the results and discusses the empirical findings; Section 3.8 concludes.

3.2 Theoretical background

In the stock-trading context, feedback trading has been used as a term to describe the conduct of a specific type of trader whose investment decisions are a function of historical prices. If he trades in the same direction with past prices he is called “positive feedback trader”, while if he trades to the opposite direction, “negative feedback (contrarian) trader”.

Although feedback trading is price-based, there is little agreement as to its practice; people do not use past prices the same way. A common tenet, however, underlying feedback trading is that the employment of past prices can yield extra insight into their future course; as a result, feedback trading *per se* runs counter to the notion of (weak-form) market efficiency.

A number of psychological biases can be associated with feedback trading. Positive feedback trading can, for example, be reinforced (Barberis et al, 1998) through the *representativeness heuristic* (overweighting recent data as representative of a trend-at-works) and the *conservatism-bias* (underweighting recent data if the perception of an opposite trend-at-works prevails). It can also be fueled by the *overconfidence-bias* (aggressive trading following an “euphoric” period of recent gains; see Odean, 1998; Glaeser and Weber, 2004a; Glaeser and Weber, 2004b). Negative feedback trading can be reinforced through the “*disposition-effect*” (preference of realizing gains through selling “winning” stocks rather than losses from selling “losing” ones; see Shefrin and Statman, 1985). Feedback trading can further be motivated through the availability of data.

Historical data on prices, for example, are easy to find in the financial press (see Huddart et al, 2002), while more sophisticated data are harder to find. Finally, the simplified analysis of such data (as carried out mostly by technical analysts in the press) facilitates the communication of these “technical heuristics” to a wider audience, which is perhaps not typified by a sufficient educational background or investment experience.

Feedback trading, however, is not restricted to noise traders who may be susceptible to behavioural biases, maintain less abilities/resources or use technical analysis. A series of papers (see e.g. Koutmos, 1997; Antoniou et al, 2005) have argued that rational traders may employ trading rules based on historical prices if they feel they have to shield themselves against (or take advantage of) abrupt market movements; portfolio insurance (Luskin, 1988) and stop-loss orders (Osler, 2002) are relevant here. Such strategic choices on behalf of rational traders are founded upon the belief that noise traders might push prices away from their fundamental value, thus leading to a mispricing of indefinite duration and magnitude (see Barberis and Thaler, 2002).

The possibility of rational “informed” traders exploiting the feedback pattern of noise traders has been addressed in the Finance literature through a series of analytical models. De Long et al (1990) assume a model where rational speculators receive a signal reflective of forthcoming information relative to a stock’s fundamentals. If the content of this signal is indicative of a rise in its price in the future, they decide to buy the stock now and sell it prior to the information going public (i.e. prior to the anticipated positive response of prices to it). However, in due course, they realize that noise traders are beginning to follow their trades as time goes by: thus, as the speculators start buying the stock, noise

traders engage in positive feedback trading and prices begin to deviate upwards from fundamentals. When the speculators start observing this trend-chasing potential, they try to exploit it by selling when the information expected is announced and then going short on that stock in anticipation of a price-reversal. De Long et al (1990) contend that this behaviour of the speculators is trend-inducing and leads to the reinforcing of positive feedback trading, upon the waves of which they are riding, thus facilitating the exacerbation of price volatility.

Farmer (2002) and Farmer and Joshi (2002) explore the possibility of the interactions of feedback traders with multiple versions of rational traders. One such version of the latter involves pursuing state-dependent threshold value strategies aimed at exploiting the perceived mispricing of a stock. More specifically, these papers assume that a rational trader who is trading upon the fundamental value of a stock is able to estimate the deviations of its price from fundamentals. If so, he may choose to take advantage of this mispricing in order to enter/exit the market before the mispricing becomes excessive. This means, for example that, instead of leaving the market in view of a mispricing, he stays on, up until his own pre-determined thresholds indicate that it is profitable to do so. This is in line with what has been mentioned previously, with respect to “rational” feedback trading using “stop-loss” orders and portfolio insurance and bears the positive effect of keeping the number of transactions (and the associated costs) to a minimum.

Andergassen (2003) devises a model similar to the one of De Long et al (1990) and finds that the longer it takes for an asset's true value to be realized by the market, the more the rational speculators feel inclined towards reinforcing trend-chasing rather than trading on fundamentals. In other words, rational

speculators may prefer to lure noise traders into a trend-chase, since they can exploit them before fundamentals become public knowledge. The difference in the behaviour of noise traders between this model and De Long et al's (1990) is that in the latter, noise traders were assumed to be of positive feedback nature while here they are assumed to exhibit a binary behaviour: either they trade on the asset's fundamental value or they engage into trend-chasing. Andergassen (2003) also finds that, if the speculators in this model act with a manipulative intent, then their impact tends to increase with their market power.

The *ad hoc* exploitation of noise traders' behaviour by rational traders who take advantage of their informational leverage is, however, only one way to view this issue. Allen and Gale (1992) have shown that an individual who is uninformed, yet imitates the trades of an informed trader, can make profits. This is possible, if he engages in *trade-based manipulation*, i.e. trying to corner the market through his buying and selling pressure without having to resort to traditional manipulative practices, such as rumour-mongering. The idea seems to be not far from the models described above, the difference being of course that the manipulator here is assumed to be uninformed. However, Allen and Gale (1992) show that, as long as he can imitate the behaviour of his informed peer, he can attract noise traders. This is supposed to be the case, if the latter misperceive him as being informed, when in fact he is not. We might contend here that this trade-based manipulator must be of a certain size in order to be able to achieve these things (i.e. know who the informed trader is, know his strategies and copy them, as well as attract noise traders).

Madrigal (1996) develops a two-period model accommodating three types of traders: a fundamentals-based informed insider, noise traders and a non-

fundamental speculator. The latter aims at inferring the insider's information through the observation of the noise traders' order-flow at period 1; using this in conjunction with the first period's price, he trades at period 2. The insider is aware of this and modifies his trades in order to manipulate the speculator's beliefs; in the end, the model shows that the speculator is likely to ride on the waves of noise and positive feedback trade, while the insider profits from this by bucking the trend.

In a paper related to Allen and Gale (1992), Mei et al (2004) show how trade-based manipulation can yield profits when used to take advantage of the behavioural biases of noise traders. The paper describes the manipulator as a trader who can exert substantial pressure on stock prices and who is using this ability of his to induce noise traders to trade in a certain direction. The authors note here that it is the disposition-effect of noise traders that constitutes the target of the manipulator, i.e. the inclination towards keeping losing stocks, while selling winning ones. Thus, the manipulator formulates a strategy based upon this bias, without relying upon fundamental information.

Hamadi et al (2005) introduce the concept of the “*illusionary*” trader, whose sole purpose is the dissemination of ambiguous (“polysemous”) signals into the marketplace in order to capture the attention of a critical mass of traders, whom they term as “*believers*”. The difference between this paper and traditional heterogeneous-agents' models is that the “believers” do not have to be noise traders, but can even fall into the category of informed ones. The idea here is that investors are under time-pressure when having to process information in order to reach a decision and, thus may include the “illusionary” information in their information-set and, perhaps, consider it to be true. As a result, illusionary trading

is not far from rumour-mongering, since both of them incorporate the concept of disseminating signals of questionable quality.

Our analysis so far has presented two types of heterogeneous-agents' models; the first, involved fundamentals-based traders intentionally exploiting noise traders by taking advantage of the informational gap between the two; the second, involved traders, who are trying to take advantage of noise traders by relying upon non-fundamental information.

We would like to draw some attention to the following: the former type of noise-traders' exploitation has been empirically tested, through the employment of real-market data (see, for example the heterogeneous-agents' models of Cutler et al, 1991; Sentana and Wadhwani, 1992; Satchell and Yang, 2003; Westerhoff, 2006) among others); we are not aware of extensive empirical research regarding the second type of noise-traders' exploitation.

To address the latter issue, we introduce a novel trader-type within an existing empirical, heterogeneous-agents' framework (that includes both rational and feedback traders in its original construction) whose trading conduct involves feedback trading when a specific threshold has been violated. This trader-type, whom we shall call "threshold trader", aims at exploiting feedback traders by trading on their trading basis (the trend) whenever a specific signal provides him with the indication that it is beneficial to do so.

Our research produces the following contributions:

- 1) introduces a novel trader-type whose trading conduct is reflective of non-fundamental, speculative behaviour
- 2) tests for its presence through the extension of an existing return-based model

- 3) empirically examines its presence across markets with differences in their heterogeneity (reflected here through the composition of investors) stemming from the differences in their regulatory structures
- 4) examines whether intertemporal changes in heterogeneity across markets affect the significance of the presence of threshold traders.

3.3 The Model

3.3.1 The original model: Sentana and Wadhwani (1992)

Our research has focused on a specific model-lineage that has evolved throughout the past decade, since it was formally introduced by Sentana and Wadhwani (1992) and has literally dominated the literature related to feedback trading, since it has been applied for a variety of markets, both developed (Koutmos, 1997; Watanabe, 2002; Bohl and Reitz, 2004; Bohl and Reitz, 2006; Antoniou et al, 2005) as well as developing (Koutmos & Saidi, 2001; Nikulyak, 2002; Malyar, 2005). Given that it bears the interesting property of addressing the issue of different trader-types' interaction in a way that allows for its enumeration using real market data, we decided to base our research upon its premises.

The model assumes two types of traders, namely “rational” ones, who maximize their expected utility and “feedback” ones who trade on the basis of lagged past returns (one period back). The demand function for the former is as follows:

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\theta \sigma_t^2} \quad (1)$$

where Q_t represents the fraction of the shares outstanding of the single stock (or, alternatively, the fraction of the market portfolio) held by those traders, $E_{t-1}(r_t)$ is the expected return of period t given the information of period $t-1$, α is the risk-free rate (or else, the expected return such that $Q_t = 0$), θ is a coefficient measuring the degree of risk-aversion and σ_t^2 is the conditional variance (risk) at time t .

The demand function of their feedback peers can be portrayed as:

$$Y_t = \gamma r_{t-1} \quad (2)$$

where γ is the feedback coefficient and r_{t-1} is the return of the previous period ($t-1$) expressed as the difference of the natural logarithms of prices at periods $t-1$ and $t-2$ respectively. A positive value of γ ($\gamma > 0$) implies the presence of positive feedback trading, while a negative value ($\gamma < 0$) would imply the presence of negative feedback (“contrarian”) trading.

In equilibrium all shares must be held; hence:

$$Q_t + Y_t = 1 \quad (3)$$

If so, then:

$$\frac{E_{t-1}(r_t) - \alpha}{\theta \sigma_t^2} + \gamma r_{t-1} = 1$$

Thus:

$$E_{t-1}(r_t) - \alpha + \gamma r_{t-1} \theta \sigma_t^2 = \theta \sigma_t^2 \Leftrightarrow$$

$$\Leftrightarrow E_{t-1}(r_t) = \alpha - \gamma r_{t-1} \theta \sigma_t^2 + \theta \sigma_t^2 \quad (4)$$

which provides us with a modified version of the CAPM in the presence of feedback traders.

Assuming $r_t = E_{t-1}(r_t) + \varepsilon_t$, we have:

$$r_t = \alpha - \gamma r_{t-1} \theta \sigma_t^2 + \theta \sigma_t^2 + \varepsilon_t \quad (5)$$

where r_t represents the actual return at period t and ε_t is the error term.

To allow for autocorrelation due to non-synchronous trading, Sentana and Wadhwani (1992) modify (5) as follows:

$$r_t = \alpha + (\gamma_0 + \gamma_1 \sigma_t^2) r_{t-1} + \theta \sigma_t^2 + \varepsilon_t \quad (6)$$

where γ_0 is designed to capture possible non-synchronous trading effects and $\gamma_1 = -\theta \gamma$.

The addition of feedback traders in an otherwise CAPM-setting bears some interesting implications. As equation (5) shows, the inclusion of the term $\gamma r_{t-1} \theta \sigma_t^2$ leads to return-autocorrelation, the magnitude of which is a function of the risk in the market (as denoted by σ_t^2). Hence, the higher the volatility grows, the higher the autocorrelation. Also the sign of the autocorrelation will be determined by the sign of the feedback trading prevalent among feedback traders: if positive feedback traders prevail, then the autocorrelation will be negative, whilst it will be positive in the presence of more negative feedback traders.

However, the feedback coefficient (γ_1) is not independent of volatility in this model. Positive feedback trading may well lead to the launch of a trend, thus forcing prices to fluctuate more wildly, hence becoming more volatile; the relationship can also assume a different form, as highly volatile markets may lead many investors to resort to strategies of positive feedback style, e.g. by employing portfolio insurance and stop-loss orders, which might cause a general price decline (in the event of a rising trend) or further exacerbate the price slump in case of a price fall.

The implications for rational traders from a rise in volatility are also obvious. As volatility rises, so does risk and, as a result, the risk-premium required on their behalf in order to hold more shares; assuming constant risk-aversion (the θ -coefficient), their ability to profit from a hypothetical trend may not be taken for granted, as the market will have grown riskier and they may well decide to liquidate their positions early on rather than follow the trend (see Kyle and Wang, 1997). Of course, as we have already argued, they might choose to stay on, in an attempt to profit from this trend, in the spirit of the “informed-based” exploitation models discussed in the previous section.

3.3.2. Threshold traders: extending Sentana and Wadhwani (1992)

Having presented the Sentana and Wadhwani (1992) model we will now attempt to introduce the “threshold” trader-type, who, as has already been suggested, becomes active once a certain threshold has been violated.

More formally, threshold traders are assumed to operate under the following demand function:

$$Z_t = \lambda r_{t-1} I_{t-1} \quad (7)$$

where λ is the threshold traders' feedback coefficient, r_{t-1} is the return of the previous period ($t-1$) expressed as the difference of the natural logarithms of prices at periods $t-1$ and $t-2$ respectively and I_{t-1} is a binary variable that is equal to:

- 1, if a given threshold has been violated at period $t-1$
- zero, otherwise

As their demand function indicates, these traders are also feedback traders (much like their "plain" feedback counterparts in the original Sentana and Wadhwani (1992) model), the sole difference being that they become active after the violation of a certain threshold.

At equilibrium, all shares must be held; therefore we will have:

$$Q_t + Y_t + Z_t = 1 \quad (8)$$

In the presence of this type of trader, equation (6) would now have to be modified as follows:

$$r_t = \alpha + (\gamma_0 + \gamma_1 \sigma_t^2) r_{t-1} + \theta \sigma_t^2 - \lambda r_{t-1} I_{t-1} \theta \sigma_t^2 + \varepsilon_t \quad (9)$$

and by substituting $\gamma_2 = -\theta \lambda$, equation (6) would now look like:

$$r_t = \alpha + (\gamma_0 + \gamma_1 \sigma_t^2) r_{t-1} + \theta \sigma_t^2 + \gamma_2 r_{t-1} I_{t-1} \sigma_t^2 + \varepsilon_t \quad (10)$$

We mentioned previously that thresholds may be employed in relation to traders' strategic behaviour, namely as a tool for exploiting (or mitigating against) mispricing. Moreover, a threshold constitutes a reference point and as such it is relevant to the biases that traders are susceptible to and the heuristics they utilize

when trying to rationalize their market environment and their investment choices (see Huddart et al, 2002).

However, the utilization of thresholds here does not restrict itself to this context only. To understand the very notion of threshold-usage in the present case, we also have to refer to biological models, most specifically those of population ecology, which entail the coexistence (symbiotic or competitive) of species (two or more) in a given environment (Edelstein-Keshet, 1987). In those models, the gains realized by one of the species (translated into “food”) have a direct impact upon their levels of participation (translated into “group size”) in their habitat.

An example here involves predator-prey settings, whose mechanism can be described as follows. Assume there exists a number of prey in the beginning, upon which the predators start preying; assuming also a constant rise in the prey’s population, the preying rate gradually increases. In view of the latter, the predators’ population rises (they are physically able to give birth to more new predators) and from a certain point onwards, this leads to the decline of the prey population’s growth. This development is detrimental for the predators’ numbers, which are then showing signs of decline as well. Given this, the prey has a chance to recover from the initial offensive and rise again numerically. Thus, both populations tend to fluctuate within a certain range, as we discussed in Chapter 2 (Edelstein-Keshet, 1987).

The point we would like to raise here is the one related to the critical thresholds, i.e. those associated with the switch in the directional evolution (increase or decrease) of the two populations. These thresholds are associated with “visibility”, i.e. the more the prey becomes after a certain point numerically the more visible it is to the predators.

Tracking down “prey” in capital markets through bare eye is obviously not a realistic option, as the number of market participants and the multiplicity of their transactions renders such a task impossible. Therefore, a trader will have to resort to an indicator of his choice in order to be able to detect the population dynamics of the conjectural “prey”.

Concurrently, the next question that arises naturally is the following: having decided to designate our hypothetical trader’s behaviour as threshold-based, which might be the most appropriate indicator to base the choice of our threshold upon?

We contend that this is an issue associated with subjective judgement. From a practical point of view, technical analysis is almost exclusively based upon price-, or joint price-volume indicators. Stop-loss orders also use prices as triggers¹⁵.

We hypothesize that volume can be a reasonable proxy as the basis for the threshold-strategy here; *more specifically, we assume that threshold traders become active once their volume-based indicator signifies the presence of rising volume*. After all, a rising volume is reflective of increased market participation and it is perhaps reasonable to assume that the more the players, the more money is on the table and hence, the more chances of reaping profits. A relative argument

¹⁵ Our hypothetical threshold trader-type is assumed to trade upon non-fundamental-based indicators; as a result, we cannot include fundamentals’ indicators (macroeconomic indicators, such as inflation and interest rates as well as company-specific indicators, such as earnings, dividends and cash flow) as possible “candidates” of their choice. However, we believe that there is a difference between using fundamental information and trading on it. A trader could, for example, use a company’s earnings in an extrapolative fashion, i.e. trying to “see” patterns in them (Barberis et al, 1998). This can, by no means, be associated with the rational, fundamentalist approach and as such could also be in line with threshold trading behaviour. Hence, then, another issue arises: can fundamentals be used by traders in a non-rational way? However, we refrain from pursuing this argument any further, as our intention here is to provide a picture of non-fundamentalist, threshold-based traders without raising similar (perhaps, arcane) considerations.

here might be that as the volume of trade rises, so does the number of active noise traders (see Wang, 2002), thus improving the chances for their exploitation.

The choice of volume has been motivated by the position it commands in the Finance literature, as it has been associated with a number of issues:

Informational content: Blume et al (1994) find that volume enhances the precision of information; thus, investors who practice “price-plus” trading (i.e. use past prices and past volume) tend to enjoy an improved informational status compared to the one they would enjoy were they to employ past prices alone. This issue has also been addressed by Antoniou et al (1997) and Gervais et al (2001) who found that past volume may well increase the potential for returns’ predictability. Chordia and Swaminathan (2000) have examined whether low-volume stock returns can be predicted by high-volume stock returns following the dissemination of marketwide information. Their presumption rests upon the speed-adjustment-hypothesis, which states that high-volume stocks respond faster to a signal than low-volume stocks. Their results have suggested that thinly-traded stocks’ returns can be predicted by examining the returns of high-volume stocks. This is also in line with what McQueen et al (1996) find, namely that small stocks tend to exhibit a temporal delay in their reaction to (marketwide) news vis-à-vis large stocks when news is good and no delay (simultaneous reaction) when news is bad (what they call “directional asymmetry”). Hameed and Ting (2000) documented a significant positive relationship between returns from a contrarian strategy and volume for the Malaysian market; thus, contrarian profits from more liquid securities were found to be higher versus those from less liquid ones.

Volatility: Another part of the volume-related research has centred its interest upon the relationship between volume and price volatility; as Karpoff (1987) has

indicated in his paper, this relationship has been found to be positive, a fact that has been denoted by a large amount of studies. Bae, Ito and Yamada (2002) find similar results when conducting a microdata study of the Japanese market as do Chan and Fong (2000) who test the relation of various volume-proxies (trade-size, trade-number and order-imbalance) with volatility.

Behavioural issues: Using a large micro-database (over 730,000 individual investors' accounts) Barber et al (2003) find among other things that individual investors in the US have the propensity to buy stocks with abnormally high trading volume as well as high past returns. The authors utilize the **attention-grabbing effect** in their attempt to interpret their results: hence, high trading volume captures investors' attention and guides them towards certain stocks. One reason, as the authors posit, is the buy-sell asymmetry; when investors wish to sell a stock, they make this choice out of a limited number of stocks already in their portfolio; however, when it comes to purchasing a new stock, the choice of it may have to be made from a larger universe of stocks. It is in this case that volume may be used as an indicator for stock-picking (high volume stocks enjoy more coverage, as they are reported through the financial press).

Barber and Odean (2003) used a proportional micro-database (727,000 individual investor accounts and 43 professional money managers' accounts) and reported similar results for the trading behavior of individual investors in the US.

Statman et al (2004) find that individual security turnover is positively related to past (market and security) returns, with the impact of a market return shock (defined as being equal to one-standard deviation) bearing an effect over future volume for up to six months in the US. The case of volume rising after high past market returns is explained here through the concept of overconfidence that



was mentioned in the beginning: high past returns (thus, higher gains) may lure more investors into the market, thus fueling the volume of trade.

Our discussion above has, thus illustrated that the volume of trade constitutes a variable capable of allowing investors extra insight into the behaviour of securities' prices. Even though other variables could be employed to proxy as indicators for the threshold-based strategy delineated previously, we argue that the choice of volume here satisfies our fundamental assumptions about the nature of our threshold-trader. Being a non-fundamental speculator, his aim is to time his feedback trading in order to potentially exploit noise trader activity without relying upon fundamental information. In this respect, we believe that volume constitutes a legitimate proxy, as it is a variable of non-fundamental content capable of capturing behavioural traits of potential noise trader activity (Barber et al, 2003; Barber and Odean, 2003; Statman et al, 2004).

3.4 Hypotheses

Given the above, we formally state our hypotheses:

1. *threshold traders are found to exhibit discernible behavioural patterns (irrespective of statistical significance) across various rising volume levels*
2. *if threshold traders are, indeed found to exhibit discernible behaviour across various rising volume levels, then there are specific rising volume levels at which their presence becomes statistically significant*
3. *if hypotheses 1 and 2 hold, then this can be attributed to the differences in the heterogeneity (and heterogeneity-related, regulatory features) of each market*

4. *threshold traders' behaviour changes across time as a result of the changes in market-heterogeneity over time*
5. *threshold traders are found to exhibit discernible and statistically significant behaviour during periods of extreme market events*

The first hypothesis states that in order for the threshold traders to be considered a distinctive group within a market, their presence must adhere to a certain pattern whenever the volume of trade exhibits a rise, regardless of its level; how this “pattern” will be considered is something we shall refer to in more detail in the next section. Suffice to say for the moment that this hypothesis tries to identify the general behavioural direction of threshold trading. It is also in line with the “informational” and “behavioural” aspects of volume discussed previously, according to which volume can provide extra insight into price movements and, as such, may be utilized as an ancillary variable for trading purposes.

The second hypothesis tries to identify whether threshold traders become statistically significant at certain rising volume levels (assuming their trading exhibits a discernible behavioural direction). The idea here is quite straightforward: if hypothesis 1 is confirmed and threshold traders are found to exhibit uniformity in their behaviour, then it is reasonable to assume that this uniformity presents itself significantly at specific (rising) volume levels.

The third hypothesis explores whether the findings of the first two hypotheses can be attributed to the differences in the regulatory framework of each market and, concurrently, its heterogeneity.

The fourth hypothesis investigates whether intertemporal differences in a market's heterogeneity (as reflected through investors' composition) can be associated with differences in the behaviour of threshold traders over time.

Finally, the fifth hypothesis states that threshold traders' behaviour during periods of extreme events is reflecting a pattern that is both distinctive (see Hypothesis 1 above) as well as statistically significant. The idea here is simple: extreme events are associated with high volatility and, as mentioned previously there is a positive relationship between volatility and the volume of trade (see Section 3.3.2). Since threshold traders are designated to be trading anytime their volume-based indicator signifies the presence of rising volume, it would be interesting to see if their behaviour exhibits any distinctive pattern during those volatile periods.

3.5 Market-heterogeneity: which markets and why

We mentioned previously that the threshold-traders' hypothesis shall be examined in markets with differences in their "heterogeneity" and we identified the latter term with the composition of investors in each market. We shall now present evidence related to the degree of heterogeneity inherent in three markets, namely Hong Kong, South Korea and Taiwan. These are the markets for which we will be testing the presence of threshold traders and we deem it appropriate to explain: a) why we selected them and b) how they differ among themselves both in terms of the regulatory provisions that impact upon market-heterogeneity as well as in terms of market-heterogeneity itself.

We will begin by explaining why we chose to work with Asian markets. A number of studies (Koutmos and Saidi, 2001; Richards, 2005) have shown that

Asian markets in general (these three markets included) accommodate substantial positive feedback trading. If so, then the potential for trend-chasing and its concurrent exploitation is existent; since threshold traders are designated to be “trading-on-the-trend” we consider the focus on this region’s stock markets to be justified.

The fundamental reason related to the selection of those three markets is the array of their differences in terms of heterogeneity and heterogeneity-related, regulatory features. We shall begin first by providing a brief description of market-heterogeneity as a term.

We have already noted that we identify market-heterogeneity with the composition of investors in a market. The composition itself is usually based upon the identity (individual/institutional) and the origin (indigenous/overseas) of market participants. Investors’ composition is calculated here on the basis of turnover-value, i.e. using proportions of the value (in \$USD) of the total annual turnover activity. The choice of turnover-value as a proxy here was made in order to enumerate the presence of various investor-types through their active participation in the trading process, not their equity-holdings (i.e. market capitalization); another reason related to the fact that investors’ composition (when available) is mostly given in terms of turnover-value.

However, the problem of comparability among markets with respect to their heterogeneity arises. How can we establish, for example, whether one market is more “heterogeneous” than another? To that end, we link the “degree” of heterogeneity of a market to the percentage of *overseas investors*¹⁶ over time. The

¹⁶ In practice, the bulk (90% or more) of overseas traders’ participation, as Table 3.1 indicates, is of institutional origin.

reason for it is that (as will be shown shortly) those traders are the ones most affected by regulatory restrictions related to market-entry and/or trading conduct and as a result, changes in those restrictions over time are assumed to be related to changes in their participation-levels.

The institutional features we are investigating here as relevant to market-heterogeneity pertain to specific regulatory provisions, namely: entry restrictions, investment restrictions, tax-provisions, as well as market frictions (e.g. price limits). Such restrictions place limits on the entry and the trading conduct, especially of foreign investors, thus reducing their scope for activity in a market-and, consequently, limiting its heterogeneity.

We will explore threshold trading in those three markets within a time-window corresponding to a period following the “opening” of those markets to overseas investors; we chose the period commencing on May 2nd 1995 and ending on December 31st 2003 (as shall be denoted later, this choice was also related to data availability). We argue that the coexistence of multiple trader-types in a market is a function of its heterogeneity, the latter being the byproduct of a market’s regulatory framework. Since our hypothetical threshold traders constitute a testable “extra” trader-type, it would be interesting to examine its presence across three markets with different regulatory structures (and, as a result, degrees of heterogeneity) during a period of ongoing financial liberalization for them.

To gain a better picture of the differences in the regulatory features that affect the heterogeneity of each market, we shall now present a brief overview of those features for each of the three markets during the 1995-2003 period.

Table 3.1: Investors' composition for Hong Kong, S. Korea and Taiwan (% of market trading value)

Types of investors ¹	Year ⇌	1995	1996	1997	1998	1999	2000	2001	2002	2003
Local individuals	HK	33	34	53	41	45	49	36	32	30
	SK	63	66	69	72	72	66	66	64	57
	TW	91.93	89.25	90.73	89.73	88.23	86.1	84.41	82.3	77.84
Local institutions	HK	33	26	20	22	18	18	19	24	28
	SK	19	15	12	8	13	12	10	9	11
	TW	6.69	8.62	7.55	8.63	9.36	10.27	9.69	10.05	11.51
Overseas institutions	HK	28	30	19	31	30	28	38	35	35
	SK	9	11	13	14	10	17	19	21	26
	TW	1.37	2.12	1.71	1.62	2.4	3.62	5.89	6.68	9.41
Overseas individuals	HK	2	2	3	2	1	2	3	2	4
	SK	2	3	2	3	2	2	2	3	3
	TW	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.97	1.24

Sources: Ho, R.Y.W., Strange, R. and Piesse, J.: "The Structural and Institutional Features of The Hong Kong Stock Market: Implications for Asset Pricing", Working Paper, King's College London, Department of Management, 2002; Hong Kong Stock Exchange Factbook 2003; Korean Stock Exchange, Taiwan Stock Exchange. NB.: The proportion of turnover-value attributable to other trader-types (e.g. members' principal trading) is not included here, as we wish to focus on the major categories of market participants (foreign-local, individual-institutional); thus, the sum of each trader-type's percentages for each market for each year may not equal 100%. Abbreviations: HK = Hong Kong, SK = South Korea, TW = Taiwan

Hong Kong

Investors did not face price limits, trading halts or circuit breakers when trading in the Hong Kong market during the 1995-2003 period (Ho et al, 2002). Brokerage fees represented a minimum of approximately 0.25% of transaction value; since April 2003 they became freely negotiable (Ho et al, 2002); neither capital gains nor personal dividends were taxed.

Overseas investors did not face any entry restrictions with regards to capital flows or foreign exchange transactions (Chui and Wei, 1998) when deciding to trade in the Hong Kong Stock Exchange (HKSE, hereafter). As a result, one would expect to encounter a substantial proportion of foreign investors in Hong Kong; Table 3.1 is indicative of this.

According to this table, overseas investors accounted, on average, for 33% of the total turnover value of the HKSE for the 1995-2003 period; subtracting their (relatively minuscule) individual component, we find that the average proportion of overseas institutional traders during that period was equal to nearly 31%. When the total institutional component of the HKSE is taken into account, we find that, on average, during that period, it accounted for 53.5% of the total turnover value (local individuals accounted, on average, for 39% of the total turnover value during that period). As a result, the HKSE included a substantial institutional (overseas, by majority) component in its investors' population over the entire period.

No restrictions are known to have been imposed to overseas traders (or any other trader-type for that purpose) with regards to the conduct of trade. Short-selling has officially been allowed since January 3rd 1994 (11th and 15th Schedules of the Rules Regulations and Procedures of the HKSE Ltd)¹⁷ and is applicable to stocks specifically designated by the HKSE whose list is updated periodically. Although most Asian markets¹⁸ impose restrictions on short-sales, this does not seem to be the case with Hong Kong.

South Korea

Price limits were applied in the Korean market; during the 1995-2003 period, the trading band for each stock was set to ± 12 percent (± 15 percent since September 1998). Trading halts and circuit breakers were also provided by the market's regulation. Securities' transaction tax was around 0.3% of the sales'

¹⁷ Source: HKSE website (<http://www.hkex.com.hk>)

¹⁸ See Morgan Stanley's report: <http://www.oecd.org/dataoecd/5/43/18465550.pdf>

proceeds. Brokerage commissions were estimated to be around 0.4% of the transaction's value on average for off-line and 0.1% for on-line transactions. Capital gains taxes applied only when the investor was a non-individual (i.e. corporate/institutional entity), while dividend-taxes were applied to all investors¹⁹.

For a foreign trader to transact, registration with the Financial Supervisory Service was required in order to obtain an Investment Registration Certificate²⁰ with an ID-number. To further be able to trade, he needed to designate a standing proxy as well as open an account with a local securities' firm. Overseas investors were subject to certain ownership limits regarding their aggregate investments within the 1995-2003 period; these, however, were subject to gradual increase²¹ and since May, 25 1998 have virtually been abolished, with the exception of specified limits of investment in certain industries deemed of strategic importance²² for which *ad hoc* laws had been passed. Short-sales were allowed (as part of rules on margin trading) only to individual investors subject to restrictions²³; foreigners were not allowed to engage in margin transactions.

Given the above, we expect the number of overseas investors in the Korean market to be rising during the 1995-2003 period as a number of

¹⁹ For more information, see the 2002-(p.63) and 2004-(p.63) Reports as well as the 2002-(p.45-46) and 2003-(p.49) Fact Books of the Korean Stock Exchange.

²⁰ Resident traders of non-Korean nationality were exempted from this requirement.

²¹ Separate ownership limits existed for each overseas investor individually and for overseas investors as a group. For more information, see the 2002-(pp.59-60) and 2004-(pp.61-62) Reports of the Korean Stock Exchange.

²² These industries (Electricity, Telecommunications, Broadcasting, Airlines and Tobacco) allowed foreign investors to maintain a maximum percentage of their shares outstanding; the percentage for each foreign investor ranged between 1% and 15% (for many companies no data on those ceilings of investment were available), while for foreign investors as a group it ranged between 15% and 49.99%. For more information, see the 2002-(pp.59-60) and 2004-(pp.61-62) Reports of the Korean Stock Exchange.

²³ For more information, see the 2002-(p.31) Report as well as the 2002-(p.25) and 2003-(p. 28) Fact Books of the Korean Stock Exchange.

restrictions have been gradually relaxed. Table 3.1²⁴ is indicative of this; as the table shows, resident individual investors maintained a clear majority in the value of transactions (on average, 66% between 1995 and 2003). The corresponding figures for foreign (most of whom institutional (Choe et al, 2004) investors and local institutional investors were 16% and 12%, respectively, with foreign investors becoming more active especially after year 2000. A series of microdata-based studies related to the Korean market (Yung and Innwon, 2000; Kim and Wei, 2002a; Kim and Wei, 2002b; Chae and Lewellen, 2004; Choe et al, 2004; Richards, 2005) indicate a strong propensity towards positive feedback trading on behalf of institutional investors in that market.

Taiwan

Price limits were applied in the Taiwanese market during the 1995-2003 period; the upper limit remained fixed throughout the period at +7%, while the lower limit exhibited certain fluctuations: it equaled -7% until 27/9/1999, -3.5% until 9/10/1999, reversed to -7% until 20/3/2000, then back to -3.5% until 1/4/2000 and (back again) to -7% afterwards. Securities' transaction tax was around 0.3% of the sales' proceeds. Brokerage commissions were estimated to be around 0.14% of the transaction's value on average. Capital gains taxes were non-existent, while dividends were subject to a withholding tax²⁵.

Overseas investors were subject to entry restrictions during the 1995-2003 period. According to the regulations regarding foreign investment in 1995, foreign institutional investors who met certain requirements (Qualified Foreign

²⁴ The proportions of investor-types was derived using back-of-the-envelope calculations from the data of the buy/sell transactions (value) for separate investor categories; the data was retrieved from the website of the Korean Stock Exchange.

²⁵ For more information, see the 2003-(p.43-44) Fact Book of the Taiwan Stock Exchange.

Institutional Investors-QFIIs) could invest directly any amount between 5 and 200 million \$USD; investments on behalf of QFIIs were subject to “ceilings” (QFIIs as a group could not invest more than 3 billion \$USD; their investments could not represent more than 12% of shareholder-ownership in aggregate and 6% individually)²⁶. Foreign individuals and foreign corporations were allowed to invest in the market directly only after March 1996; their investment ceiling was defined as equal to 5 million \$USD annually, while the ceiling for QFIIs was raised on that year to 400 million \$USD as were their ownership limits (to 25% for shareholder-ownership in aggregate and 10% individually). Restrictions also applied with regards to specific industries²⁷; what is more, foreign investors were not allowed to engage in short-selling²⁸. As of 2003, the government promised to abolish the QFII-system to allow for greater flexibility in foreign participation, while a new categorization imposed allowed for the classification of foreign investors into four categories contingent upon their status (foreign institutional versus overseas Chinese and foreign individual) and their residence (onshore versus offshore). Relevant investment limits apply; overseas Chinese and foreign individuals are not allowed to invest more than 5 million \$USD, while there exist limits for foreign institutional investors only if they are “onshore” (50 million \$USD).

Table 3.1 depicts the proportions of investors of various types over the 1995-2003 period based upon the annual turnover-value. Given the previous discussion regarding investment limits, we would expect foreign investors to

²⁶ Source: http://www.duke.edu/~charvey/Country_risk/chronology/taiwan.htm

²⁷ Ceilings for foreign ownership in brackets: Cement and Minerals (50%), Shipping (one-third), Inland Transportation (foreign investment not allowed) and Utilities ($\leq 49.99\%$).

²⁸ The discussion so far is based on evidence documented in the website of the Taiwanese Stock Exchange.

constitute a small part of the total investors' population. Indeed, as the table shows, domestic individual investors represented, on average, approximately 87% of the total turnover value; the corresponding proportions for domestic institutional and foreign (institutional, in their supreme majority) traders were 9% and 4% on average, although one should also note that overseas institutional participation seems to be rising after year 2000. According to a number of microdata-based studies (Yang, 2002; Lin, 2003) investors in Taiwan engage in feedback trading although there seems to be little agreement as to its direction among various investor types. Domestic individual traders do not seem to be able to exploit their dominant position; Lee et al (2003) and Barber et al (2004) find that they are noise traders who incur losses when transacting with their institutional counterparts.



Having presented the three markets, we shall now attempt to provide a brief comparative picture of them on the grounds of market-heterogeneity and the regulatory features relevant to it, as presented thus far (a summary of what follows can be found in Table 3.2).

Entry restrictions: First of all, given our previous discussion, it is evident that of all the three markets, it is Hong Kong that appears to be the most liberal one in terms of entry restrictions for foreign traders. Contrary to Hong Kong, the other two markets are typified by a number of barriers related to the entry of foreign investors. Nevertheless, one should note that the other two markets (especially the Korean one) have undergone some major regulatory reforms throughout the 1990s that have rendered them more open to overseas investment.

Table 3.2: A summary of the heterogeneity-related regulatory features of Hong Kong, South Korea and Taiwan

Regulatory features related to heterogeneity ↓	Markets ⇒	Hong Kong	South Korea	Taiwan
Entry restrictions		None	Overseas investors: individual and group quotas (terminated after May 1998); industry-specific investment ceilings remain	Overseas traders: QFII; new categorization of as of 2003; investment-ceilings; individual and group quotas
Investment restrictions		Short-selling allowed only on ad hoc designated stocks	Institutional traders not allowed to sell short; overseas traders not allowed to engage in margin transactions	Overseas traders not allowed to sell short
Trading restrictions		None reported	Price-limits, circuit-breakers, trading-halts	Price-limits
Tax-provisions		No capital-gains- or dividend-taxes	Capital-gains tax applicable to non-individual traders; dividend-tax applicable to all traders	No capital-gains tax; dividend-tax existent
Transactions costs (expressed here as brokerage fees)		0.25% of transaction-value (until April 2003)	Approx. 0.4% of transaction-value (0.1% for online transactions)	Approx. 0.14% of transaction-value

Sources: see Section 3.5

Investment restrictions: When it comes to restrictions regarding the trading conduct, Hong Kong maintains its characteristic as the most “liberal” of the three

markets in our sample, as no material barriers to the conduct of trade for any type of investors have been documented. In comparison, South Korea and Taiwan retain a series of restrictions regarding the mode of trade, especially that of foreign investors.

Tax-provisions: Regarding taxation, the provisions related to it are found to be substantially less in Hong Kong (no capital gains' or dividends' tax) compared to South Korea and Taiwan.

Heterogeneity: With regards to the composition of investors, again here we note the apparent difference between Hong Kong and the other two markets; Hong Kong is characterized by an average majority of institutional (mostly foreign) investors, while South Korea and Taiwan maintain a dominant (indigenous) individual component²⁹.

Therefore, our analysis has shown us that the degree of heterogeneity of a market (as measured by the proportion of overseas trading volume) seems to be *a positive function of the degree of market liberalization*. Hong Kong appears to be the most “heterogeneous³⁰” (and “liberal”) of the three markets; Taiwan still maintains substantial restrictions regarding overseas investors while South Korea has undertaken significant liberalization measures and can be assumed (in a schematic sense) to stand in-between Hong Kong and Taiwan in terms of heterogeneity³¹.

²⁹ However, it is worth noting that the overseas component is growing in all three markets from year 2000 onwards. Whether this is due to the relatively low prices in those markets in the aftermath of the Asian crisis (1997) that prompted foreign traders to (re-)invest in the region is not something we can be assertive about; all the same, though, it remains a possible explanation.

³⁰ With the highest average overseas trading volume (approx. 31%)-see previous section.

³¹ Note here that the discussion pertains to the 2/5/1995-31/12/2003 period; as a result, post-2003 changes are not taken into account.

The rationale for testing the relation between threshold trading and market heterogeneity (as a function of a market's institutional settings), thus becomes more apparent in view of the above discussion. Threshold trading *per se* constitutes a version of feedback trading and, as such, is expected to exhibit certain differences across markets with different institutional settings. This is because the latter have the potential of influencing feedback trading patterns through their entry/trading restrictions (which mostly tend to affect foreign traders).

A market where overseas traders are subject to entry-quotas renders the practice of any type of feedback trading (indeed, trading itself, in general) on their behalf problematic, since a foreign trader who wishes to feedback-trade in such a market may not be able to do so due to entry- (if the entry-quota for foreign investors has already been filled) or trading-restrictions (he may not be able to trade because the price limit for the day has been "hit"). Another reason as to why he may not be able to trade is because short-selling may be proscribed in that market³². If short-selling is not allowed, the very practice of threshold trading is compromised, as threshold traders will be unable to sell when the threshold's violation indicates a sell-signal. With respect to short-sales, we would like to note here that they constitute an important element in the trading process, since they allow for the expression of the "pessimistic" part of the investors' population (see Miller, 1977; Gervais et al, 2001). In other words, if investors are not allowed to sell short, an imbalance is bound to arise, as the "sell-force" of the market will be deprived of a trading tool; as this implies a rise in the significance of the "buy-

³² Most Asian markets maintain severe restrictions over short-selling; see the the previous mention to Morgan Stanley's report on the region.

force”, the possibility of a mispricing (upwards) increases. If threshold traders cannot sell short (in accordance with their threshold-indication), then obviously there is little point in using it. Thus, any restrictions on short-sales impede the expression of wider heterogeneity in the market, as part of it is not able to trade in a way consistent with its beliefs.

Thus, institutional restrictions have the potential of reducing the scope for the uninhibited practice of feedback trading. Although the practice of certain “stylized” (i.e. adaptive to market-specific conditions) feedback strategies³³ cannot be overruled, we contend that liberal market environments are expected to be more conducive to the practice of different types of feedback trading, by allowing for wider market participation. As a result, threshold trading, being feedback in its essence, may as well be exhibiting differences in its presence across markets with different institutional settings, as well as within the same market across time as its structure is subject to regulatory reforms.

3.6 Methodology and Data

3.6.1 Methodology

In order to test for threshold trading, we use the modified Sentana and Wadhwani (1992) model; recall that, according to the specification defined in equation (10):

³³ *If a market operates under price limits, then a feedback trader might devise a trading strategy such that it would allow him to take advantage of these limits. Price limits make it easier to “programme” pre-specified profit-levels, since the price-range for each day is pre-defined. If the upper price limit, for example, is set at 5%, the market is experiencing an upward trend and a feedback trader would like to realize profits of, say 20 %, all he has to do is wait for at least four days before he sells. This way, his feedback trading is conditioned upon a certain target, which in turn is conditioned upon the movements of prices within a specific price-band.*

$$r_t = \alpha + (\gamma_0 + \gamma_1 \sigma_t^2) r_{t-1} + \theta \sigma_t^2 + \gamma_2 r_{t-1} I_{t-1} \sigma_t^2 + \varepsilon_t$$

According to the Sentana and Wadhwani (1992) model $\gamma_1 = -\theta \gamma$ (implying that, if γ_1 is negative, the sign of feedback trading is positive) and according to our substitution in (10) $\gamma_2 = -\theta \lambda$ (implying also that if γ_2 is negative, the sign of the feedback trading of threshold investors is positive). Thus, we are testing for the null hypothesis, namely that $\gamma_2 = 0$ (i.e. there are no threshold traders) versus the alternative one that $\gamma_2 \neq 0$ (there are threshold traders). We shall also be referring to the results of the feedback (γ_1) coefficient in order to see if there is any association between its results and the results of the threshold coefficient (as both of them relate to the same feedback demand function).

The conditional variance σ_t^2 is modeled here as an EGARCH-process (Nelson, 1991, Brooks, 2002):

$$\ln \sigma_t^2 = \omega + \xi \ln \sigma_{t-1}^2 + \psi (u_{t-1} / \sqrt{\sigma_{t-1}^2}) + \kappa * [(|u_{t-1}| / \sqrt{\sigma_{t-1}^2}) - \sqrt{2/\pi}] \quad (11)$$

EGARCH allows for asymmetric responses of volatility to positive and negative shocks, since if the volatility-returns relationship is negative, ψ will be negative as well³⁴. As standardized residuals from GARCH-models tend to exhibit signs of leptokurtosis, we estimate the EGARCH-model by assuming a Generalized Error Distribution (GED).

The indicator upon which thresholds are calculated in our tests originates from technical analysis. Our threshold traders-given their demand function-are, in

³⁴ The EGARCH falls within a large family of GARCH volatility-measures allowing for asymmetric effects of volatility. The asymmetric effect relates to the situation where volatility exhibits larger increases for negative returns compared to (equally large) positive returns. Such a fact has been associated with leverage-effects at the corporate level (Brooks, 2002), since large price declines would be expected to inflate the debt-equity ratio. For more on this, see Kasch-Haroutounian and Price (2001).

essence, feedback traders and, as such, trade on the basis of past prices. Feedback trading, as an umbrella-term, covers technical analysis³⁵; consequently, the fact that threshold traders associate feedback trading with technical thresholds cannot be considered inconsistent. Having said that, we, by no means imply that threshold traders are technical traders, necessarily. It could as well be the case that they are informed traders capitalizing on the technical heuristics widely available to the public with the purpose of exploiting them-and the public.

The technical indicator upon which the grounds of our threshold trading hypothesis are tested is called *volume-ratio* (VR) and is calculated by dividing the volume of trade by its moving average. The purpose of this ratio is *to measure the amount of volume relative to its historical moving average*, thus inferring the magnitude of its increase / decrease over time. It follows that: $VR = V / MA$, where VR is the ratio's value, V is the volume of trade and MA is the corresponding moving average of the volume.

An issue here arises regarding the calculation of the moving average. Technical analysts employ a variety of moving average specifications, such as simple, exponential, triangular, variable, weighted, adaptive, and endpoint moving averages. Here, we test for the significance of threshold traders on the basis of volume-ratios whose moving averages in the denominator follow two specifications, namely simple and exponential³⁶. The employment of two specifications hinges upon the fact that the very specification itself might bias the

³⁵ Given the almost mystical properties that technical analysis attributes to past prices regarding their predictive ability it has also come to be known as "voodoo finance" (see Westerhoff, 2006).

³⁶ These are the two specifications that appear with greater frequency in technical analysis sources. The following technical analysis websites were consulted in order to construct our volume-thresholds: <http://www.stockcharts.com/>, <http://trading-stocks.net/firms.com/>, <http://www.linnsoft.com/>, <http://www.marketscreen.com/>, <http://www.equis.com/>, <http://www.incrediblecharts.com/>, <http://www.investopedia.com/>, <http://www.tadoc.org/>, www.prophet.net/.

results, i.e. a market might for some reason generate significant results for one specification and not for another.

A brief note on the moving average construction follows.

-Simple Moving Average: it represents the mean value of a variable for a given number of periods over time. A volume-ratio whose moving average component is of this specification will be called *simple volume-ratio*, will be denoted as **VR** and will be followed by a number, designating the number of periods (in our case, days) for which it is calculated.

-Exponential Moving Average: it is calculated as $EMA(t) = [(VALUE(t) - EMA(t-1)) * Multiplier + EMA(t-1)]$, where VALUE here stands for the value of the variable under study (i.e. trading volume) and the Multiplier is calculated as: $[2 / (Time Periods^{37} + 1)]$

A volume-ratio whose moving average component is of this specification will be called *exponential volume-ratio*, will be denoted as **EVR** and will be followed by a number, designating the number of periods (in our case, days) for which it is calculated.

We chose four different lengths of moving averages to work with, namely 10, 20, 150 and 200 days. For the purpose of comparability as well as behavioural monitoring, we group volume ratios into two categories, namely “short” and “long” ones. More specifically, “short” volume ratios include moving averages of

³⁷ Time periods for which the moving average is calculated.

10- and 20-days length, while “long” ones include moving averages of 150- and 200-days length. We, thus test for two different versions of threshold traders, those using short and those using long volume ratios.

We noted in a previous section (3.3.2) that threshold traders are designated to become active anytime the volume of trade exhibits a rise. In view of that, we test for the significance of threshold trading for volume ratio values **in excess of 1.0**, i.e. when the volume of the previous day ($t-1$) is above its contemporaneous (at time t) moving average; the latter implies a rise in the level of volume with respect to its underlying moving average. *Thus, “rising” volume levels are associated here with those volume levels for which the volume of trade is above its moving average.* We also test for ratio-values *0.5 times apart* (i.e. lagged volume being 1.0, 1.5, 2.0 and so on times greater than its contemporaneous moving average³⁸) in order to test for the consistency of threshold traders’ behaviour across various rising volume levels (above the underlying moving average) in accordance with our first hypothesis. For brevity reasons, we shall be referring to the various volume ratio values we will be testing for as “ranks”.

To visualize both the concept of those “ranks” and the evolution of a given volume ratio over time, Figures 3.1 and 3.2 provide us with the plots of the 20- and 200-day simple volume ratios for Hong Kong during the sample period (2/5/1995 – 31/12/2003). Table 3.3 provides us with some descriptive statistics

³⁸ *The rationale of the tests here is as follows: by dividing the volume by its moving average, we get the time series of the volume ratio which we plot on a chart. We, then, scale the chart-area for VR-values of 0.5; if the highest observation of the VR on the plot crosses the line of, say, 3.0 but does not reach the line of 3.5, we perform our tests only up to rank 3.0.*

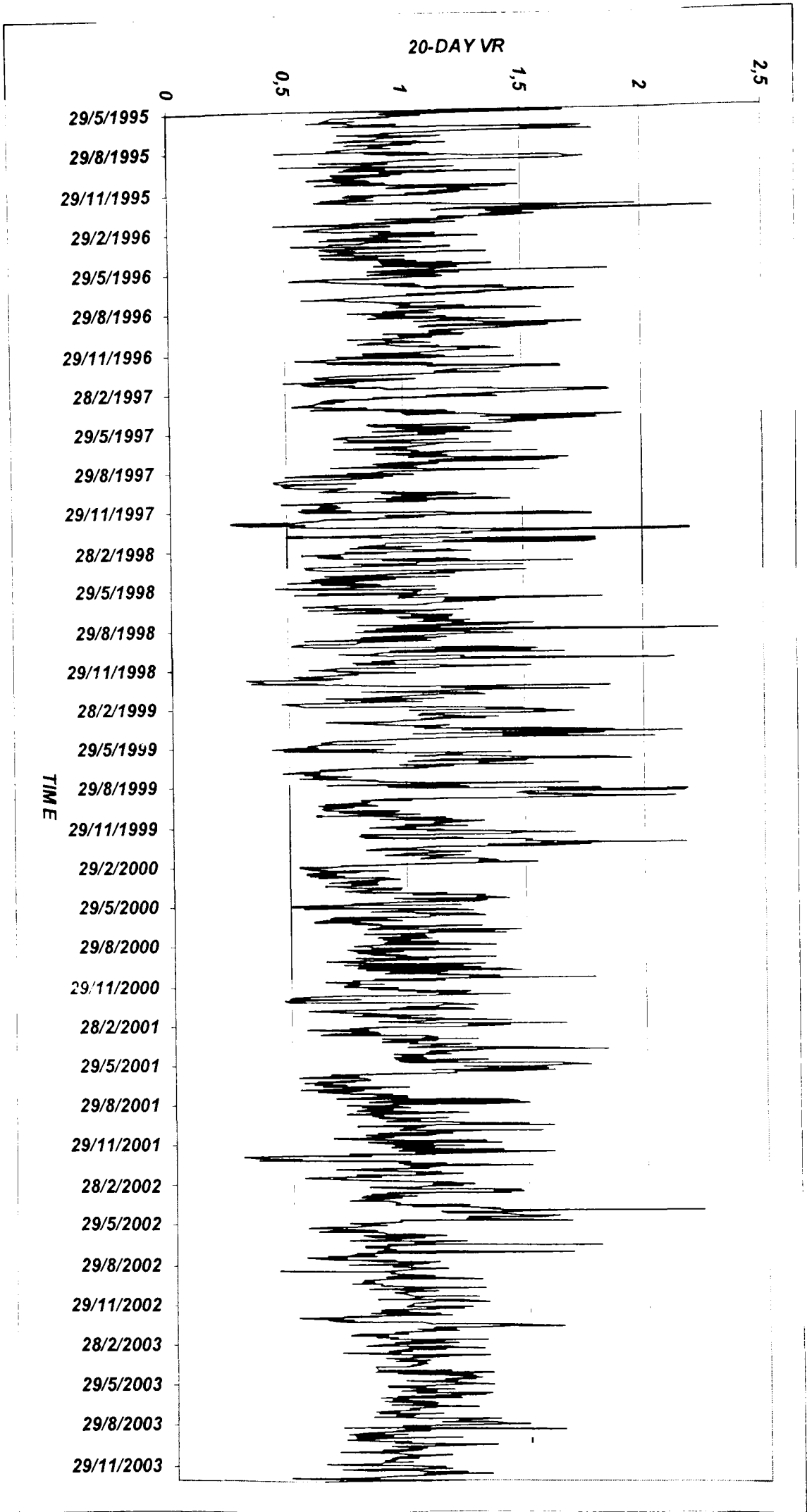


Figure 3.1: Hong Kong 20-days Simple Volume Ratio (2/5/1995-31/12/2003)

Figure 3.2: Hong Kong 200-days Simple Volume Ratio (2/5/1995-31/12/2003)

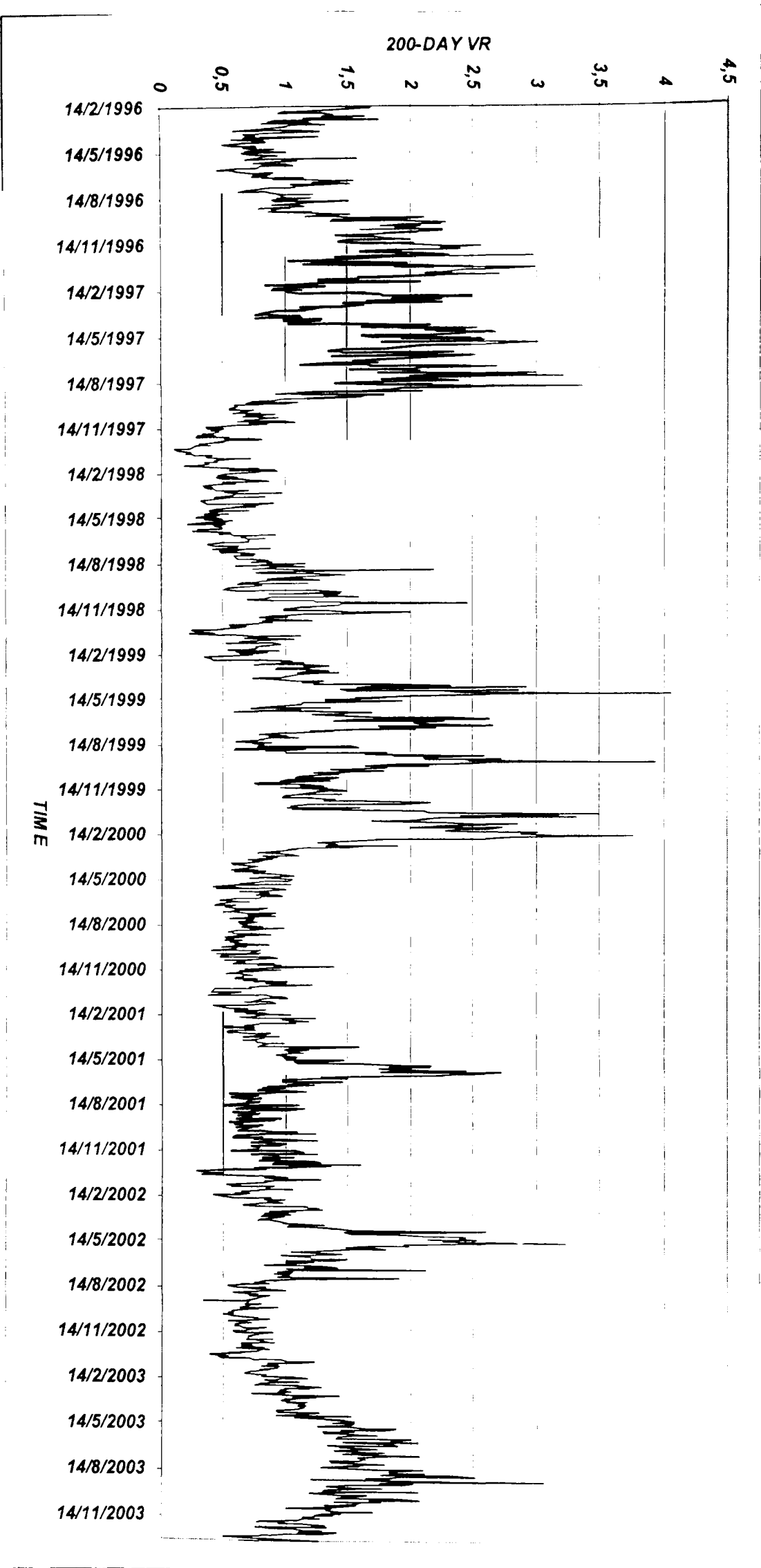


Table 3.3: Descriptive Statistics of the Hong Kong 20- and 200-days Simple Volume Ratios (2/5/1995-31/12/2003)

	20-day VR		200-day VR	
Number of observations	2122		1942	
Mean	1,019752187		1,143904522	
Maximum	2,312575626		4,053395487	
Minimum	0,260605697		0,109380819	
Standard Deviation	0,298210634		0,600905068	
Ranks (of rising volume levels)				
Rank	Number of Observations	% of total sample observations	Number of Observations	% of total sample observations
1.0	1005	0,473609802	930	0,478887745
1.5	148	0,069745523	442	0,227600412
2.0	14	0,006597549	213	0,109680742
2.5			69	0,035530381
3.0			20	0,010298661
3.5			4	0,002059732
4.0			1	0,000514933

with respect to the 20- and 200-day simple volume ratios on the premises of rising volume ratio ranks 0.5 times apart.

As the table indicates, the number of observations decreases, as the rank grows. One might postulate that the higher volume ratio ranks correspond to volume-spikes related to high volume levels compared to the volume's historic average.

We mentioned previously (Section 3.4) that we wish to test for the *discernibility* of threshold traders' behaviour across various rising volume levels (Hypothesis 1). The term *discernibility* refers here to the uniformity of the sign of the threshold coefficient across various "ranks" for each volume ratio category (short/long); since threshold traders operate on the basis of a feedback function, their sign can be either positive or negative (indicative of negative or positive feedback trading, respectively). Thus, *discernibility* here is associated, essentially, with the appearance of a consistent positive/negative threshold sign in all tests across all ranks for a specific category (short/long) of volume ratios.

As far as Hypothesis 2 is concerned, we have to note the following. For a discernible threshold pattern to manifest itself significantly at a specific rank, its significance must be evident in, *at least, three out four volume ratios of its category*. This is because we would like to mitigate against possible length- or specification-biases, which would be the case, for example if: a) the threshold coefficient were to be significant for two volume ratios of that rank and b) both of them were of identical length/specification.

Hypotheses 4 and 5 shall be tested through the break-up of the full-sample period, in line with these hypotheses' content.

We have already noted that the degree of a market's heterogeneity over time shall be denoted by the levels of overseas investors' participation. In conjunction with hypothesis 4, we test for the significance of the presence of threshold traders across sub-periods characterized by differences in market-heterogeneity, as indicated by Table 3.1. The choice of sub-periods here adheres to a certain logic: the "cutoff" point is not traced at the beginning of the year at the end of which there appears to be a surge in the ranks of overseas investors, but rather at the beginning of the next year. The point here is to ensure that the period following this "cutoff" point involves a surge that exhibits continuity (i.e. perseveres during the following years). More specifically, we test for Hypothesis 4 by assuming the following periods for each market:

Hong Kong: 2/5/1995-31/12/2001, 1/1/2002-31/12/2003. According to Table 3.1, overseas investors exhibit a rather abrupt rise by year-end 2001, which continues until the end of our sample period.

South Korea: 2/5/1995-31/12/2000, 1/1/2001-31/12/2003. According to Table 3.1, overseas investors exhibit a rather abrupt rise by year-end 2000, which continues until the end of our sample period.

Taiwan: 2/5/1995-31/12/1999, 1/1/2000-31/12/2003. According to Table 3.1, overseas investors exhibit a slight rise by year-end 1999, which continues until the end of our sample period.

With regards to Hypothesis 5, we chose the Asian crisis period as the proxy-period for extreme market events. We assume the window between 2/7/1997-31/12/1998 as the "in-crisis" window in line with Lin (2003) who also includes substantial referencing on the issue of this window-choice. Tests are

conducted for all three markets to evaluate the behaviour of threshold traders within this period, as well as before and after it.

Finally, with regards to Hypotheses 4 and 5 we would like to note that, in case we identify a discernible threshold pattern during a sub-period, the significance of which manifests itself at specific volume ratio ranks, we will perform Wald tests to assess the significance of the difference between the threshold coefficients in that period with those in the other period/s at those ranks.

3.6.2 Data

Our data relates to the all-shares' indices³⁹ of Hong Kong (AOI), South Korea (KOSPI) and Taiwan (TAIEX); all data have been obtained from the DataStream database as well as from the respective websites of the aforementioned stock exchanges⁴⁰ and involve daily observations of index closing prices and turnover by volume (number of shares traded).

Data on market-specific investors' composition (Table 3.1) were retrieved from the respective websites of the three stock exchanges.

Our sample covers the period between 2/5/1995 and 31/12/2003 and corresponds to the post-liberalization era for Asian markets. This period allows us to examine threshold trading when the underlying market-heterogeneity tended to increase with financial liberalization (see also Holmes and Wong, 2001). Another issue relevant to our choice relates to the fact that data on investors' composition

³⁹ *The choice of indices (and not, for instance, individual stocks) is due to the fact that the Sentana and Wadhvani (1992) model has so far been tested only for market indices (be they all-shares or size-/sector-specific) and, hence, in the interest of comparability with existing results it would be better to test for similar data-types as well.*

⁴⁰ Hong Kong: <http://www.hkex.com.hk/index.htm>, South Korea: <http://sm.krx.co.kr/>, Taiwan: <http://www.tse.com.tw/ch/index.php>.

was only available from 1995 onwards for Hong Kong and Taiwan and this prompted us to select this as the starting year of our sample. To ensure comparability among all three markets, we chose May 2nd 1995 to be our starting date, as volume-data for the Korean market were available after that date.

3.6.3 Descriptive statistics

Descriptive statistics for the daily index returns of the three markets are provided in Table 3.4. The statistics reported are the mean (μ), the standard deviation (σ), measures for skewness (S) and kurtosis (K) and the Ljung–Box (LB) test statistic for ten lags. The skewness and kurtosis measures indicate departures from normality (returns-series appear significantly negatively skewed and highly leptokurtic).

Rejection of normality can be partially attributed to temporal dependencies in the moments of the series. It is common to test for such dependencies using the Ljung–Box portmanteau test⁴¹ (LB) (see Bollerslev et al., 1994). The LB-statistic is significant for the returns-series of Hong Kong and South Korea, but not Taiwan. This provides evidence of temporal dependencies in the first moment of the distribution of returns, due to, perhaps nonsynchronous trading or market inefficiencies. However, the LB-statistic is incapable of detecting any sign reversals in the autocorrelations due to positive feedback trading. It simply provides an indication that first-moment dependencies are present. Evidence on

⁴¹ The LB-test is used to test for serial correlation in the residuals of a time series and is estimated on the premises of the following test-statistic: $Q_m = T(T+2) \sum_{k=1}^m (\rho(k))^2 / (T-k)$, where T is the sample size, $\rho(k)$ is the autocorrelation at lag k and m is the number of lags being tested. The serial correlation hypothesis is accepted if $Q_m > \chi^2_{1-\alpha, m}$, where α is the significance level for which the test is undertaken on the basis of the chi-square distribution.

higher order temporal dependencies is provided by the LB-statistic when applied to squared returns. The LB-statistic is significant for the returns-series of all markets without exception. Moreover, it is, always higher than the LB-statistic calculated for the returns, suggesting that higher moment temporal dependencies are more pronounced.

Table 3.4: Sample statistics: daily index returns (2/5/1995 to 31/12/2003)

	Hong Kong	South Korea	Taiwan
μ	0.01861956882	-0.0052838901	0.00096167055
σ	1.63527552863	2.3020763828	1.72628073744
S	-0.19281***	-0.05891	-0.02285
K	8.46232***	2.61103***	1.84935***
LB(10)	37.90720324***	34.38004325***	14.91266497
LB ² (10)	747.708837***	453.9265829***	254.2939828***

(* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level). μ = mean, σ = standard deviation, S = skewness, K = excess kurtosis, LB (n) and LB²(n) are the Ljung-Box statistics for returns and squared returns respectively distributed as chi-square with n degrees of freedom where n is number of lags

3.7 Results

3.7.1 Threshold trading: Discernibility and statistical significance

To provide ourselves with an initial picture of the presence of feedback trading in our three markets, we tested the Sentana and Wadhwani (1992) model in its original form for the 2/5/1995-31/12/2003 period; results are reported in Table 3.5. The coefficients describing the conditional variance process, ω , ξ , ψ and κ , are all statistically significant (1% level) in all cases, with the exception of ω in South Korea. Note also that ψ is negative and statistically significant for all three markets, implying that negative innovations tend to increase volatility more than positive ones. The feedback coefficient is indicative of positive feedback trading in all three markets, significantly so in Hong Kong and Taiwan, yet not in South Korea.

We shall now present the results from our empirical tests of the Sentana and Wadhwani (1992) model with threshold traders (hereafter, “modified” Sentana and Wadhwani (1992) model). Before we commence our discussion, we would like to note that each of the tables to follow shall effectively illustrate the

Table 3.5: Maximum likelihood estimates of the original Sentana and Wadhwani (1992) model

Parameters ↓ —	Markets ⇒	Hong Kong	South Korea	Taiwan
α		0.029321601 (0.029629286)	-0.060509119 (0.055912349)	-0.066348831 (0.033442054)**
γ_0		0.183243634 (0.024166163)***	0.136500697 (0.031175545)***	0.129452393 (0.038837463)***
γ_1		-0.020242033 (0.005395382)***	-0.005741185 (0.004320923)	-0.023993738 (0.010330039)***
θ		-0.007653401 (0.015727495)	0.008568138 (0.014183904)	0.022177797 (0.005064823)***
ω		0.021951709 (0.006176947)***	0.017639890 (0.010959954)	0.055621590 (0.020934652)***
ξ		0.976095941 (0.006853162)***	0.991268403 (0.006211526)***	0.947689070 (0.020612340)***
ψ		-0.082021654 (0.015821697)***	-0.036426920 (0.013336760)***	-0.084546356 (0.020084740)***
κ		0.177961936 (0.023186226)***	0.142391350 (0.036036599)***	0.175576566 (0.037996758)***

(* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level). Parentheses include the standard errors of the estimates; sample period: 2/5/1995-31/12/2003.

$$r_t = \alpha + (\gamma_0 + \gamma_1 \sigma_t^2) r_{t-1} + \theta \sigma_t^2 + \varepsilon_t$$

$$\ln \sigma_t^2 = \omega + \xi \ln \sigma_{t-1}^2 + \psi (u_{t-1} / \sqrt{\sigma_{t-1}^2}) + \kappa * [(|u_{t-1}| / \sqrt{\sigma_{t-1}^2}) - \sqrt{2/\pi}]$$

results from the modified model's tests regarding the feedback and the threshold coefficients only⁴²; the white rows in each shall correspond to the feedback coefficient (γ_1) results while the shaded ones to the threshold-coefficient (γ_2) results of the modified Sentana and Wadhwani (1992) model.

As Tables 3.6 and 3.7 indicate, the feedback coefficient (γ_1) appears to be overtly tilted towards positive feedback trading (its sign is found to be negative for all tests in all ranks for all volume ratios, be they short or long); its statistical significance manifests itself in Hong Kong⁴³ and Taiwan⁴⁴, while South Korea failed to provide us with significant results. The results for the feedback coefficient are in line with those documented previously from the tests with the original Sentana and Wadhwani (1992) model.

Hong Kong threshold traders appear to be adhering to a constant negative feedback trading pattern when we test for short volume ratios. Indeed, a quick inspection of Table 3.6 reveals that all threshold coefficient results are uniform in sign (positive); however, it is at rank 1.0 that the statistical significance of the threshold coefficient appears to be "clustering". At that rank, the threshold coefficient is statistically significant (5% level) for the VR10, EVR10 and the VR20. As a result, when short volume ratios are utilized, Hong Kong threshold traders exhibit a behaviorally discernible (negative feedback trading) pattern, which is found to be statistically significant at rank 1.0 (VR10, EVR10, VR20).

⁴² Reasons related to space-considerations prevent us from outlining the results for all coefficients for both the return as well as the conditional variance equation. Our intention here is to present results that shall: a) depict the overall feedback direction of each market's index and b) indicate the direction (positive/negative feedback) of threshold trading at various volume ratio ranks.

⁴³ At the 1% level for short and at the 5% level for long volume ratios.

⁴⁴ 10% level for both short and long volume ratios.

Since no statistical significance was encountered for the threshold coefficient at rank 1.5 for two (VR10, VR20) out of those three volume ratios, we ran further tests using the area between ranks 1.0 and 1.5 as a threshold; results revealed that the significance of the threshold coefficient documented above persisted within the area between ranks 1.0 and 1.5 for all three volume ratios. When long volume ratios were tested, Hong Kong provided us with no discernible threshold trading pattern⁴⁵, while evidence of statistical significance for the threshold coefficient appeared scant across our results (see Table 3.7).

South Korean threshold traders do not adhere to any discernible behavioural pattern for either short or long volume ratios; their statistical significance is limited and mostly concentrated at the top ranks of both short and long volume ratios. Rank-specific patterns do arise; however, absent the one at rank 3.0⁴⁶ for long volume ratios (which provides us with a statistically significant-at the 5% level-positive feedback pattern), the rest (ranks 1.0⁴⁷ and 1.5⁴⁸ for short and ranks 2.0⁴⁹ and 2.5⁵⁰ for long volume ratios) lack statistical significance (see Tables 3.6 and 3.7).

Taiwanese threshold traders also do not demonstrate any discernible behavioural pattern across either short or long volume ratios, while their statistical significance is limited for short volume ratios and is mostly concentrated at the top ranks (3.0-3.5⁵¹) of long volume ratios. Rank-specific patterns do arise;

⁴⁵ Nevertheless, there appear to be certain rank-specific patterns (rank 1.0: positive feedback trading; ranks 2.0 and above: negative feedback trading), albeit weakly statistically significant.

⁴⁶ Corresponding to the observation of the 16/1/1998.

⁴⁷ All threshold coefficients indicative of positive feedback trading.

⁴⁸ All threshold coefficients indicative of positive feedback trading.

⁴⁹ All threshold coefficients indicative of negative feedback trading.

⁵⁰ All threshold coefficients indicative of positive feedback trading.

⁵¹ The observations corresponding to rank 3.0 of the long volume ratios in Taiwan are:

VR150 (rank 3.0): 8/4/1996, 20/11/2001 and 26/11/2001.

EVR150 (rank 3.0): 8/4/1996

however, absent the ones at ranks 3.0 and 3.5 for long volume ratios (which provide us with a statistically significant-at the 5% level-positive feedback pattern), the rest (ranks 1.0⁵² and 1.5⁵³ for short and ranks 1.5⁵⁴ and 2.0⁵⁵ for long volume ratios) lack statistical significance (see Tables 3.6 and 3.7).

Thus, it appears that South Korea and Taiwan fail to reveal any discernible, behavioural pattern for threshold trading across all ranks for both short as well as long volume ratios and, as a result, we fail to accept the first and the second hypotheses for these two markets. Contrary to South Korea and Taiwan, a discernible behavioural (negative feedback) pattern surfaces in Hong Kong across all ranks of short volume ratios; this pattern becomes statistically significant at rank 1.0 and corresponds to a substantial number of our sample's observations (approximately 47% for rank 1.0⁵⁶, depending upon the volume ratio's length and specification). In other words, threshold traders in Hong Kong appear to be negative feedback trading anytime the volume of trade exceeds its 10- and 20-day simple and exponential moving average. Consequently, we argue that the first and the second hypotheses can be accepted for the Hong Kong market.

VR200 (rank 3.0): 8/4/1996 and 26/11/2001

EVR200 (rank 3.0): 8/4/1996

⁵² *All threshold coefficients indicative of positive feedback trading.*

⁵³ *All threshold coefficients indicative of negative feedback trading.*

⁵⁴ *All threshold coefficients indicative of negative feedback trading.*

⁵⁵ *All threshold coefficients indicative of positive feedback trading.*

⁵⁶ *Approximately 43% for the 1.0-1.5 area, depending upon the volume ratio's length and specification.*

3.7.2 Threshold trading and the differences in heterogeneity across markets

Our analysis in Section 3.5 indicated that Hong Kong is the market with the least heterogeneity-related, regulatory restrictions. Contrary to that, the other two markets imposed certain limits both in the entry and the trading practices of investors during the 1995-2003 period, with direct implications, especially upon the participation levels of overseas investors as summarized in Section 3.5. This means that, if a trader wished to implement the threshold-strategy, he would have to consider issues, like entry restrictions (e.g. amount of capital invested, investment ceilings) as well as trading restrictions (e.g. short-sales' prohibition, price-limits).

Consequently, the regulatory framework in Hong Kong allows for minimal obstacles in the presence and activity of the threshold-trader type, thus providing it with the opportunity of pursuing its trading pattern without restrictions. As our results from the previous section indicated, when short volume ratios are used, Hong Kong threshold traders are found to exhibit a discernible pattern, whose statistical significance can be identified at certain volume ratio levels; since none of the other markets is reflective of any such pattern, this, by itself, provides us with the ground to accept the third hypothesis, namely that the possibility of associating the discernibility (and, concurrent, significance) of threshold trading across markets with differences in the regulatory framework (and, thus, heterogeneity) does exist. However, heterogeneity (much like a market's regulatory structure) is not something static; it evolves over time and it is this very

Table 3.6: Short volume ratio results (2/5/1995-31/12/2003)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20
3.0							-0.004317557 (0.002609507)*					
							0.610800061 (0.307037990)**					
2.5					-0.005688767 (0.004861589)		-0.004317557 (0.002609507)*					
					0.585889735 (0.357065009)		0.610800061 (0.307037990)**					
2.0	-0.020408357 (0.006111918)***		-0.020265903 (0.005447789)***	-0.020642914 (0.006014149)***	-0.005692825 (0.004852827)	-0.005689004 (0.004477825)	-0.004400149 (0.003537173)	-0.005747117 (0.004249100)			-0.023655688 (0.007924184)***	-0.023956605 (0.009991963)**
	0.136625423 (0.190138945)		0.009189075 (0.092259180)	0.334865593 (0.195500010)*	0.579866975 (0.325156977)*	0.585942526 (0.387216620)	-0.034874236 (0.024778741)	0.119873507 (0.015009904)***			-0.053714390 (0.087336387)	0.053287623 (0.268895088)
1.5	-0.021558590 (0.006741057)***	-0.020863592 (0.004573088)***	-0.021240809 (0.005464027)***	-0.020285676 (0.006296628)***	-0.005603016 (0.004828571)	-0.005481212 (0.004467044)	-0.005090491 (0.004460538)	-0.004735357 (0.005019397)	-0.024429524 (0.008265823)***	-0.024614481 (0.010098495)**	-0.024360955 (0.009750489)**	-0.024751933 (0.011155926)**
	0.013060366 (0.018284425)	0.009902276 (0.004697133)**	0.004609185 (0.004201763)	0.000667621 (0.015588193)	-0.002878252 (0.012805535)	-0.008810003 (0.020414317)	-0.003878580 (0.007480550)	-0.014805294 (0.002103315)***	0.045618420 (0.022200902)**	0.066068929 (0.037136252)*	0.005362490 (0.017171415)	0.024501768 (0.021522494)
1.0	-0.032347772 (0.006718913)***	-0.031015279 (0.006821223)***	-0.030671570 (0.006696880)***	-0.022123051 (0.006188894)***	-0.004065060 (0.004509887)	-0.003775071 (0.006018439)	-0.004939905 (0.006458492)	-0.002588349 (0.001855718)	-0.020159350 (0.008917646)**	-0.020502959 (0.012302297)*	-0.019231297 (0.011550892)*	-0.020929343 (0.012528507)*
	0.017488896 (0.006653072)***	0.015567136 (0.006707506)***	0.015525102 (0.006650089)**	0.004159044 (0.007039569)	-0.002266714 (0.005995069)	-0.003013498 (0.006358309)	-0.001253288 (0.004578797)	-0.003972796 (0.002531765)	-0.007574255 (0.010247114)	-0.006243178 (0.011614623)	-0.010075688 (0.011107133)	-0.005209349 (0.010900253)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 2/5/1995-31/12/2003. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

Table 3.7: Long volume ratio results (2/5/1995-31/12/2003)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200
3.5			-0.020224428 (0.006207679)***		-0.005216066 (0.003786496)		-0.005550517 (0.004535725)	-0.000060257 (0.000283692)	-0.023043444 (0.006272290)***	-0.023042517 (0.008039524)***	-0.023042517 (0.008039524)***	-0.023042517 (0.008039524)***
			0.232901794 (0.241600030)		-0.099421124 (0.009709830)***		-0.017734683 (0.022608563)	-0.105724371 (0.040744646)***	-0.359807582 (0.096484663)***	-0.359812664 (0.119818433)***	-0.359812664 (0.119818433)***	-0.359812664 (0.119818433)***
3.0	-0.020774312 (0.005230125)***		-0.020300411 (0.005433727)***	-0.020467309 (0.006226496)***	-0.006162079 (0.001533449)***	-0.002519419 (0.003188880)	-0.005510534 (0.004441737)	-0.005243669 (0.004664356)	-0.023473140 (0.011866351)**	-0.023042517 (0.008039524)***	-0.023042517 (0.011551189)**	-0.023042517 (0.008039524)***
	0.124384987 (0.120483316)		0.009217899 (0.053126470)	0.014726555 (0.059517384)	-0.048101482 (0.015659784)***	-0.102513165 (0.023847021)***	-0.005190562 (0.007318812)	-0.048004272 (0.019377953)**	-0.214717306 (0.093256191)**	-0.359812664 (0.119818433)***	-0.260559912 (0.122553805)**	-0.359812664 (0.119818433)***
2.5	-0.021012991 (0.006253974)***	-0.020484568 (0.008682314)**	-0.020832561 (0.003859961)***	-0.020902250 (0.005553052)***	-0.005085329 (0.004577830)	-0.005515472 (0.004946409)	-0.005082067 (0.004561930)	-0.005615733 (0.004642153)	-0.023862164 (0.009945955)**	-0.023964976 (0.007302231)***	-0.023881707 (0.009680284)**	-0.023898858 (0.007958794)***
	0.042261052 (0.025609117)*	0.016497022 (0.092680159)	0.031923913 (0.029762426)	0.039425093 (0.038335278)	-0.007548317 (0.014372552)	-0.003411402 (0.014771343)	-0.006655736 (0.003223323)**	-0.002038559 (0.004885189)	-0.021679956 (0.061345759)	0.000611353 (0.115483503)	-0.019413414 (0.052452988)	0.065432208 (0.091243532)
2.0	-0.020511139 (0.005655149)***	-0.020792683 (0.006050549)***	-0.020389916 (0.004797216)***	-0.020812556 (0.006318630)***	-0.001909381 (0.000437607)***	-0.007717531 (0.004024943)*	-0.005929529 (0.005198825)	-0.006574440 (0.004974795)	-0.023985343 (0.010396280)**	-0.023983085 (0.009031647)***	-0.023996625 (0.009563562)**	-0.023971292 (0.020821626)
	0.050764194 (0.028654284)*	0.038881950 (0.030868663)	0.026957230 (0.025965833)	0.039082786 (0.031751423)	0.000966062 (0.000777782)	0.007819940 (0.008852163)	0.000665674 (0.006843110)	0.003341744 (0.007040411)	-0.002359397 (0.030116444)	-0.013080417 (0.044103734)	-0.002913603 (0.040554624)	-0.009535148 (0.151133770)
1.5	-0.019919443 (0.004177378)***	-0.020659073 (0.005774637)***	-0.019854677 (0.005405273)***	-0.019924018 (0.005594481)***	-0.009519872 (0.006069981)	-0.008308849 (0.006046908)	-0.005146075 (0.006076085)	-0.008308849 (0.007840998)	-0.023155850 (0.010227894)**	-0.025298964 (0.009528733)***	-0.024013449 (0.009917455)**	-0.025549722 (0.010754331)**
	-0.005658470 (0.015994705)	0.012065037 (0.019665969)	-0.010873948 (0.015453667)	-0.006736812 (0.019835542)	0.006681759 (0.006306890)	0.001067100 (0.006300038)	0.004391993 (0.005312719)	-0.001086192 (0.004005947)	-0.023334367 (0.014330073)	-0.031367128 (0.017763035)*	-0.012853554 (0.013139180)	-0.035504137 (0.020700009)*
1.0	-0.019321813 (0.004713688)***	-0.017476491 (0.006341948)***	-0.018167934 (0.006131948)***	-0.017476066 (0.005473075)***	-0.009163957 (0.007725839)	-0.006391229 (0.007550233)	-0.005616078 (0.007870964)	-0.008258309 (0.007060130)	-0.025087027 (0.005331465)***	-0.025116884 (0.006715124)***	-0.021112315 (0.010962011)*	-0.023993521 (0.008667983)***
	-0.019890646 (0.013195941)	-0.016704030 (0.011319551)	-0.013863551 (0.005187569)***	-0.017297098 (0.011371509)	0.004122062 (0.006232050)	0.000739329 (0.006147577)	-0.000142002 (0.006981681)	0.002791651 (0.005381335)	0.004679158 (0.009944189)	0.004751870 (0.009165857)	-0.013254405 (0.010917819)	0.000168528 (0.009703713)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 2/5/1995-31/12/2003. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

evolutionary relationship between threshold trading and market heterogeneity that the next part of our discussion shall try to investigate.

3.7.3 Threshold trading and intertemporal changes in market-heterogeneity

If hypothesis 3 is a mere identification of the possibility of relating threshold trading with the underlying heterogeneity of a market, it is interesting to study whether this possibility can be supported empirically, i.e. whether the behaviour of threshold traders (as documented by our results so far) is subject to changes intertemporally as a market's heterogeneity changes over time. To that end, we split the sample window for each market into two sub-periods (before and after the rise in overseas investors' participation) using the "cutoff" points indicated in our discussion in Section 3.6.1 and tested our modified Sentana and Wadhwani (1992) model for both sub-periods. We shall now review our results on the basis of each of the two sub-periods.

3.7.3.a First sub-period: limited overseas investors' participation

The results for the feedback coefficient for all three markets for the period prior to the rise in overseas investors' participation are indicative of overt positive feedback trading (see Tables 3.8 and 3.9), which is found to be statistically significant in Hong Kong (1% level) and Taiwan (5% level) for both short and long volume ratios; for South Korea, results indicate very limited statistical significance for both short and long volume ratios.

When short volume ratios were tested, the results for the threshold coefficient for Hong Kong indicated the presence of an overt negative feedback trading pattern across all ranks whose statistical significance tended to “cluster” at rank 1.0. The latter constitutes an identical picture with our previous findings for the full-period tests and implies the existence of a discernible and significant (1% level) negative feedback pattern at rank 1.0. Since no statistical significance was encountered for the threshold coefficient at rank 1.5 for two (VR10, VR20) out of those three volume ratios, we run further tests using the area between ranks 1.0 and 1.5 as a threshold; results revealed that the significance of the threshold coefficient documented above persisted within the area between ranks 1.0 and 1.5 for all three volume ratios. When long volume ratios were tested, the results for the threshold coefficient for Hong Kong did not produce any discernible threshold patterns.

The results for the threshold coefficient for South Korea seem to indicate the absence of any discernible threshold pattern when we tested for short volume ratios⁵⁷. When long volume ratios were tested, our results were similar, only that now we noticed a “clustering” of its statistical significance at the top ranks of each long volume ratio, which provided us with an indication of a discernible positive feedback pattern at those ranks.

The results for the threshold coefficient for Taiwan indicate the absence of any discernible threshold patterns when short volume ratios are used; actually, the threshold coefficient does not appear to be statistically significant in any of the tests performed. When long volume ratios are tested, the results for the

⁵⁷ *Note also the scant evidence of statistical significance for the threshold coefficient (Table 3.8).*

threshold coefficient indicate the presence of a near-overt⁵⁸ positive feedback trading pattern across all ranks whose statistical significance tends to emerge mostly at the top ranks.

3.7.3.b Second sub-period: increased overseas investors' participation

The results for the feedback coefficient for all three markets for the period following the rise in overseas investors' participation, are indicative of overt, yet (mostly) statistically insignificant, positive feedback trading for both short and long volume ratios (Tables 3.10 and 3.11). The results for the threshold coefficient for all three markets seem to indicate the absence of any discernible significant threshold pattern for both short as well as long volume ratios; actually statistical significance⁵⁹ appears rather scattered throughout our threshold-coefficient results, as Tables 3.10 and 3.11 illustrate.

An interesting first observation here is the one related to the feedback coefficient, which, although overtly indicative of positive feedback trading during both periods in all markets, is found, in the cases of Hong Kong and Taiwan, to lose its statistical significance in the aftermath of the rise in overseas investors' participation⁶⁰.

⁵⁸ The sign of the threshold coefficient at rank 2.5 for the EVR150 is indicative of negative feedback trading.

⁵⁹ Perhaps the only case worth mentioning here is the one of Taiwan when long volume ratios are tested; the results for the threshold coefficient indicate the appearance of statistical significance mostly at the top ranks; again, as for the period prior to the rise in overseas investors' participation, their sign is still mostly indicative of positive feedback trading, with the same exception (top rank \rightarrow 2.5) for the EVR150, which, as for the first sub-period, is still indicative of negative feedback trading.

⁶⁰ Similar results were obtained when running the original Sentana and Wadhwani (1992) model for the two sub-periods for each market.

Table 3.8: Short volume ratio results (limited overseas investors' participation)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20
3.0							-0.003456555 (0.003967025)					
							0.166816526 (0.290177724)					
2.5					-0.003421789 (0.003674133)		-0.003456487 (0.004153129)	-0.003604276 (0.004680043)				
					0.667700247 (0.338480485)**		0.166802153 (0.295640787)	0.166207118 (0.299954610)				
2.0	-0.019664162 (0.005104380)***		-0.019575163 (0.006067724)***	-0.019867582 (0.004967964)***	-0.003573223 (0.003261607)	-0.003603908 (0.004450779)	-0.003330540 (0.004349100)	-0.003604707 (0.004376056)			-0.049868008 (0.018994525)***	-0.050127608 (0.022595067)**
	0.124877526 (0.147369156)		0.011149569 (0.064304827)	0.325660471 (0.157259221)**	0.660651346 (0.423694435)	0.166236079 (0.326148217)	-0.043866309 (0.028517349)	0.160592935 (0.313080024)			0.005803807 (0.172590236)	0.056262870 (0.246095056)
1.5	-0.020717164 (0.005982659)***	-0.020081785 (0.005836010)***	-0.020237218 (0.005936877)***	-0.019577428 (0.005292717)***	-0.003318344 (0.004278271)	-0.003202580 (0.003673604)	-0.003167208 (0.004321268)	-0.002250057 (0.003653990)	-0.052607711 (0.021113287)**	-0.052007894 (0.021098012)**	-0.048209569 (0.019476983)**	-0.051851053 (0.021749383)**
	0.012956903 (0.016710453)	0.007867719 (0.004034182)*	0.004416675 (0.011655666)	0.000341512 (0.015304985)	-0.007304651 (0.017119353)	-0.016379614 (0.020858837)	-0.003751361 (0.009084242)	-0.021643817 (0.011391410)*	0.054641039 (0.043477001)	0.067005920 (0.069201991)	-0.015539952 (0.025984854)	0.024282436 (0.035129458)
1.0	-0.028671761 (0.004139429)***	-0.028541083 (0.003444916)***	-0.028579185 (0.004068990)***	-0.020238704 (0.006240341)***	-0.001603691 (0.005308414)	-0.000655563 (0.005620466)	-0.000680658 (0.001327611)	0.000183114 (0.005255803)	-0.046464013 (0.011518060)***	-0.048191994 (0.021661007)**	-0.048204741 (0.023367514)**	-0.050396023 (0.022138505)**
	0.014398228 (0.004006097)***	0.013545771 (0.003002757)***	0.015094590 (0.004764215)***	0.001872314 (0.006303555)	-0.003395283 (0.006490097)	-0.004796518 (0.005938578)	-0.004066373 (0.002738836)	-0.005628151 (0.005378925)	-0.010856701 (0.015738028)	-0.006211938 (0.016775701)	-0.006831260 (0.018189529)	-0.002479778 (0.016352572)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

Table 3.9: Long volume ratio results (limited overseas investors' participation)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200
3.5			-0.019523817 (0.005382831)***		-0.002988870 (0.002790727)		-0.003353310 (0.004035628)	-0.000884808 (0.000422876)**	-0.047663811 (0.023052190)**	-0.047663811 (0.023052190)**	-0.047664017 (0.021045398)**	-0.047664055 (0.022864030)**
			0.228667165 (0.175976719)		-0.094906130 (0.015311766)***		-0.023799850 (0.016850643)	-0.097154810 (0.007400856)***	-0.269490845 (0.114858478)**	-0.269490845 (0.114858478)**	-0.269490471 (0.113141404)**	-0.269489070 (0.119015840)**
3.0	-0.020104793 (0.005740005)***		-0.019599117 (0.005369997)***	-0.019771899 (0.004788902)***	-0.003354508 (0.003844224)	-0.003553030 (0.001335481)***	-0.003214120 (0.004337859)	-0.003200308 (0.004893440)	-0.047663811 (0.023052190)**	-0.047663811 (0.023052190)**	-0.047664017 (0.021045398)**	-0.047664055 (0.022864030)**
	0.108723793 (0.102523437)		0.006909363 (0.046274789)	0.014182955 (0.005677372)**	-0.023540505 (0.020643921)	-0.094463244 (0.007027354)***	-0.008203070 (0.014942705)	-0.042484710 (0.017085059)**	-0.269490845 (0.114858478)**	-0.269490845 (0.114858478)**	-0.269490471 (0.113141404)**	-0.269489070 (0.119015840)**
2.5	-0.020345409 (0.005250575)***	-0.019774096 (0.004486497)***	-0.020013653 (0.006136734)***	-0.020334436 (0.005559143)***	-0.002975025 (0.003977896)	-0.003743300 (0.004293062)	-0.002632537 (0.004109418)	-0.003878655 (0.002556754)	-0.048960721 (0.023461077)**	-0.049974862 (0.022954266)**	-0.048978331 (0.019298560)**	-0.049757993 (0.021222480)**
	0.038613121 (0.023864238)	0.014230024 (0.006390021)**	0.027669177 (0.029956131)	0.036035439 (0.026860994)	-0.007134544 (0.011250985)	0.001797246 (0.013148764)	-0.008570543 (0.011112613)	0.002033964 (0.001811515)	-0.128418766 (0.149036512)	0.012794734 (0.128365473)	-0.158739796 (0.134555957)	-0.022118700 (0.138236265)
2.0	-0.020144052 (0.005421915)***	-0.020188431 (0.005361676)***	-0.019867397 (0.004511074)***	-0.020150090 (0.005946665)***	-0.004140679 (0.004549245)	-0.004983671 (0.004820757)	-0.004102611 (0.005507257)	-0.003820286 (0.004350119)	-0.050707872 (0.023188335)**	-0.053335729 (0.024878115)**	-0.050151918 (0.019326587)***	-0.050521565 (0.021819795)**
	0.045677443 (0.024147282)*	0.034654881 (0.023408021)	0.019715127 (0.022845075)	0.033480987 (0.026802384)	0.002225997 (0.007353243)	0.004316990 (0.007936984)	0.001826240 (0.007319509)	0.001489591 (0.007258988)	-0.028069386 (0.064096499)	-0.050439960 (0.068835351)	-0.015359695 (0.056684341)	-0.032699922 (0.062601807)
1.5	-0.019441140 (0.004508293)***	-0.019687505 (0.005270665)***	-0.019304191 (0.004547895)***	-0.019452717 (0.005272634)***	-0.007027249 (0.005089486)	-0.002890379 (0.005326909)	-0.006000596 (0.005620924)	-0.001864914 (0.005491191)	-0.054014531 (0.024023369)**	-0.055003143 (0.022044290)**	-0.052268464 (0.022896748)**	-0.055093083 (0.022369953)**
	-0.003825699 (0.014366400)	0.011183968 (0.018335570)	-0.008457004 (0.014292775)	-0.004586126 (0.018266226)	0.005241772 (0.006069438)	-0.000887182 (0.004709916)	0.003582995 (0.006088982)	-0.002864448 (0.005801436)	-0.047043589 (0.027366497)*	-0.067818810 (0.029475722)**	-0.035932170 (0.034440158)	-0.062134365 (0.044777417)
1.0	-0.018564876 (0.005808630)***	-0.016463536 (0.004235677)***	-0.017529665 (0.005434494)***	-0.016544877 (0.005283343)***	-0.007021264 (0.006743342)	-0.004687446 (0.006582249)	-0.000139859 (0.007947195)	-0.004385367 (0.006860381)	-0.045806939 (0.022534007)**	-0.047732669 (0.018022859)***	-0.050853529 (0.023623108)**	-0.049493768 (0.013846665)***
	-0.019134797 (0.010464051)*	-0.016451934 (0.010281996)	-0.012912835 (0.006607362)*	-0.016846744 (0.011568419)	0.004088795 (0.007077742)	0.001214488 (0.004773407)	-0.003816466 (0.006565004)	0.000844611 (0.006322061)	-0.023923455 (0.019548899)	-0.015788067 (0.017471044)	-0.039800694 (0.025514071)	-0.019650916 (0.012026329)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

One possible explanation here might be that the increase in foreign investors' trading has led to the decline of the significance of positive feedback trading. Holmes and Wong (2001) show that the entry of foreign investors has led to a reduction of the impact of noise trading in Singapore, South Korea⁶¹ and Taiwan for the 1988-1996 period. Although our period of investigation extends far beyond 1996, the findings of that paper appear to be conceptually relevant to the ones documented previously.

With regards to the threshold coefficient, South Korea and Taiwan failed to furnish us with any discernible significant threshold patterns for both short and long volume ratios, either before or after the advent of overseas investors. On the other hand, Hong Kong produced a discernible (negative feedback) pattern observed during the period prior to the advent of overseas investors; this pattern was found to be statistically significant (1% level) at rank 1.0 of short volume ratios and involved a considerable number of our sample's observations (approximately 48% at rank 1.0⁶², depending upon the volume ratio's length and specification). Note that this pattern disappeared during the period following the rise of the foreign traders' presence in market-activity. Why this might be the case is not that straightforward. Following the Asian crisis, the Hong Kong Government resorted to a massive purchase of Hang Seng Index (i.e. high-cap) stocks in mid-August 1998 to mitigate against speculative short-selling pressure on stock prices; the divestiture of those

⁶¹ Note here that the findings of Holmes and Wong (2001) for South Korea imply that the impact of noise trading has not been significantly reduced during the post-liberalization period; interestingly enough, our findings indicate that the feedback coefficient is statistically more significant during the period following the advent of overseas investors, both with the original and the modified Sentana and Wadhwani (1992) model for this market. However, no point of comparison is possible here due to differences in sample windows.

⁶² Approximately 46% for the area between 1.0-1.5, depending upon the volume ratio's length and specification.

stocks began during 2001. If threshold traders were unable to produce any discernible significant pattern after year-end 2001, then one might argue that this might be due to the abrupt rise in overseas investment, which (for some reason) led to the demise of the first sub-period's threshold pattern.

However, when we ran Wald tests to test for the significance of the differences of the threshold coefficients for the VR10, VR20 and EVR10 at rank 1.0 for both sub-periods, we found the differences between them to be insignificant, thus casting doubt over the actual impact of the rise in overseas trading. In view of what has been said so far, therefore, we argue that we can accept the fourth hypothesis for the Hong Kong market; changes in heterogeneity do appear to influence the discernibility of threshold traders' presence over time, although its impact on the latter's significance appears questionable.

3.7.4 Threshold trading during extreme market events

The purpose here is to investigate whether the behaviour of threshold traders exhibits distinctive patterns during periods that could be characterized as "extreme". We chose the Asian financial crisis period (2/7/1997-31/12/1998) as a proxy for such "extreme" events, in line with the discussion in Section 3.6.1. To that end we tested for the significance of threshold trading by running the modified Sentana and Wadhwani (1992) model for the crisis' period, the period before it as well as the period after it. Here, we shall report our results for each sub-period (pre-, in- and post-crisis) separately.

Table 3.10: Short volume ratio results (increased overseas investors' participation)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20
2.0			-0.251493236 (0.180173621)				-0.053771698 (0.033677529)				-0.013036053 (0.011388487)	
			-0.034978503 (0.178360475)				0.011890700 (0.083697491)				-0.085980419 (0.056087772)	
1.5	-0.228758343 (0.172618773)	-0.231957571 (0.173428049)	-0.233671863 (0.175329321)	-0.234467149 (0.186123780)	-0.056623660 (0.038201687)	-0.056732208 (0.030618168)*	-0.052657809 (0.037905252)	-0.063493249 (0.038835563)	-0.014181569 (0.010507168)	-0.013815676 (0.008697189)	-0.013659837 (0.013101976)	-0.013829629 (0.010651765)
	-0.371324122 (0.229947886)	-0.299828152 (0.230448695)	-0.272465895 (0.192593108)	-0.260232466 (0.219046287)	0.022387277 (0.030013226)	0.025175865 (0.067924177)	-0.003961620 (0.026698287)	0.036415710 (0.025552428)	0.029840044 (0.022348462)	0.042163353 (0.053472712)	0.020179945 (0.018633011)	0.012793073 (0.028143250)
1.0	-0.247561263 (0.167840733)	-0.242943291 (0.180619529)	-0.251219821 (0.177384978)	-0.228337582 (0.156175133)	-0.047022857 (0.025379181)*	-0.048631674 (0.029191814)*	-0.051674855 (0.031458688)	-0.051373482 (0.058347992)	-0.015335842 (0.015095317)	-0.014785418 (0.015498578)	-0.011162046 (0.015555011)	-0.013769485 (0.014051654)
	0.089972039 (0.086138356)	0.126883386 (0.077359789)	0.000187640 (0.089148870)	0.107243881 (0.080991994)	-0.017477098 (0.018591610)	-0.011967789 (0.015695367)	-0.006265247 (0.015085381)	-0.010477721 (0.071779112)	0.004500215 (0.015537622)	0.003033462 (0.015335326)	-0.005164058 (0.012353628)	0.000405344 (0.014205592)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

Table 3.11: Long volume ratio results (increased overseas investors' participation)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200
3.0					-0.055494568 (0.043009118)		-0.053735206 (0.033384006)		-0.013460418 (0.011335004)		-0.013425428 (0.012278682)	
					-0.163793089 (0.015137170)***		0.001494934 (0.169024425)		-0.143313377 (0.001965674)***		-0.168525107 (0.034712272)***	
2.5	-0.258283972 (0.175050705)		-0.258446761 (0.190716105)	-0.261072019 (0.193536025)	-0.053106161 (0.028580949)*	-0.050543233 (0.036188541)	-0.053842963 (0.035023710)	-0.053329635 (0.030977896)*	-0.013445804 (0.012543402)	-0.013455670 (0.012239171)	-0.013085011 (0.010773710)	-0.012841203 (0.009325963)
	-0.166784807 (0.193954503)		-0.173656145 (0.141195169)	-0.272423956 (0.211183050)	-0.005894634 (0.052976573)	-0.063626934 (0.052504160)	0.001005187 (0.044525225)	-0.003619867 (0.051754638)	0.021029311 (0.082481509)	-0.134690241 (0.042080935)***	0.045961613 (0.069699269)	0.203437777 (0.081268306)***
2.0	-0.286683979 (0.217854138)	-0.261148484 (0.194402484)	-0.219369643 (0.204353337)	-0.270554589 (0.183770116)	-0.058628177 (0.021594252)***	-0.057178087 (0.033652457)*	-0.055026679 (0.039823658)	-0.057383122 (0.032719116)*	-0.013356962 (0.012866286)	-0.013530293 (0.012390582)	-0.013239388 (0.012988917)	-0.013391427 (0.012549804)
	-0.329983826 (0.205012901)	-0.190709050 (0.147480197)	0.174155349 (0.213853672)	-0.287273670 (0.186044281)	0.030004498 (0.006911540)***	0.018306075 (0.038754519)	0.004307518 (0.027373637)	0.025521215 (0.032366391)	0.013391574 (0.034245145)	0.014181370 (0.048211907)	0.015170980 (0.040425784)	0.014170656 (0.055850823)
1.5	-0.267064230 (0.235395940)	-0.264966861 (0.204937389)	-0.250084045 (0.162646242)	-0.269739486 (0.196395955)	-0.056647286 (0.030457855)*	-0.057019259 (0.033600002)*	-0.056356342 (0.038054853)	-0.056160823 (0.035832508)	-0.013511407 (0.013862562)	-0.013732627 (0.011376519)	-0.013484474 (0.010141703)	-0.013721809 (0.012393890)
	-0.045745315 (0.178280655)	-0.054320371 (0.232505008)	0.003472100 (0.085485131)	-0.073311327 (0.195209914)	0.006109397 (0.022482000)	0.014938103 (0.020929205)	0.005067402 (0.019090310)	0.009873038 (0.017851079)	-0.005204470 (0.018776366)	-0.004189141 (0.026155978)	0.002995616 (0.021580029)	-0.013067534 (0.025271074)
1.0	-0.250890685 (0.178388084)	-0.257249030 (0.164019638)	-0.252529210 (0.180107960)	-0.255046795 (0.169441578)	-0.051955704 (0.032389528)	-0.043707436 (0.028251369)	-0.051818953 (0.032943106)	-0.053508934 (0.031512863)*	-0.021563984 (0.013010638)*	-0.021418001 (0.007936868)***	-0.013849122 (0.009481078)	-0.016753757 (0.013058711)
	0.005882422 (0.092153859)	0.100157229 (0.082797345)	0.026376463 (0.089389829)	0.087344276 (0.084745871)	-0.003753911 (0.015281847)	-0.016527076 (0.014357753)	-0.003754741 (0.015265408)	-0.000380816 (0.015816730)	0.022771565 (0.013301991)*	0.022936502 (0.010818331)**	0.002193910 (0.006955040)	0.015874591 (0.013775129)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

3.7.4.a Pre-crisis: 2/5/1995-1/7/1997

The results for the feedback coefficient for all three markets for the pre-crisis period are indicative of overt positive feedback trading (see Tables 3.12 and 3.13), which is found to be statistically significant only in the case of South Korea (10% level) for both short and long volume ratios; evidence of the statistical significance of positive feedback trading (as reflected through the feedback coefficient) in both Hong Kong and Taiwan appears scant for both short and long volume ratios.

The results for the threshold coefficient for Hong Kong before the crisis indicate a rather mixed picture, with the threshold coefficient failing to align itself with any distinctive feedback direction for both types of volume ratios; statistical significance appears to be sporadic. No clear pattern appears to emerge for South Korea either, while statistical significance tends to manifest itself mostly at the top ranks of both short⁶³ and long⁶⁴ volume ratios. The results for the threshold coefficient for Taiwan indicate a pattern of overt-yet mostly insignificant-negative feedback trading when short volume ratios were used. When long volume ratios were tested, results indicated a rather mixed picture, with the threshold coefficient failing to align itself with any distinctive feedback direction; notice that, at the top ranks (3.0 and above), the indication is of statistically significant (10% level) positive feedback trading.

⁶³ Ranks 2.0 and above are indicative of statistically significant (10% level) negative feedback trading.

⁶⁴ Rank 2.5 is indicative of statistically significant (10% level) negative feedback trading.

Table 3.12: Short volume ratio results (Pre-crisis)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20
3.0							-0.084223173 (0.028424553)***					
							0.315968985 (0.063136890)***					
2.5					-0.082553997 (0.019889644)***		-0.084223173 (0.028424553)***	-0.084223173 (0.028424553)***				
					0.317188917 (0.051669039)***		0.315968985 (0.063136890)***	0.315968985 (0.063136890)***				
2.0					-0.085514854 (0.040394338)**	-0.082553997 (0.019889644)***	0.030407915 (0.011144804)***	-0.059364886 (0.019308181)***			-0.092718053 (0.044820575)**	-0.098649176 (0.044725292)**
					0.316494759 (0.049885158)***	0.317188917 (0.051669039)***	0.261411275 (0.121830464)**	0.332225928 (0.200576846)*			0.010249612 (0.217071392)	0.081837831 (0.286578168)
1.5	-0.103478716 (0.079124823)	-0.103531154 (0.078388437)	-0.096631004 (0.081400712)	-0.100836221 (0.077721234)	-0.084970121 (0.037578211)**	-0.075401056 (0.041071368)*	-0.082315698 (0.040644588)**	-0.074659507 (0.042171764)*	-0.071945403 (0.092878454)	-0.081914070 (0.176510170)	-0.079927952 (0.078647475)	-0.084245522 (0.057212864)
	0.264548015 (0.151722943)*	0.254642811 (0.185875387)	0.210174254 (0.146494995)	0.233515783 (0.139119013)	-0.014065263 (0.082131021)	0.244002620 (0.163852668)	0.055493225 (0.119660265)	0.181847449 (0.127249709)	0.054012966 (0.076161064)	0.042571084 (0.113331750)	0.046494128 (0.055866483)	0.080951267 (0.034165677)**
1.0	-0.115839402 (0.070513364)	-0.093454770 (0.072669574)	0.612281428 (0.114158383)***	-0.106679236 (0.074614193)	-0.071910165 (0.040981333)*	-0.071532802 (0.050286274)	-0.100544968 (0.041894748)**	-0.091125689 (0.046586279)*	-0.093566485 (0.118617076)	-0.097595253 (0.016467100)***	-0.095739599 (0.078687776)	-0.099269315 (0.063433583)
	0.015172989 (0.071969009)	-0.023020238 (0.070149526)	-0.019894637 (0.114827745)	-0.000645614 (0.065110000)	-0.025482831 (0.038936360)	-0.024331281 (0.041457456)	0.015928696 (0.035845846)	0.008957695 (0.036116165)	0.022343861 (0.033606738)	0.027008875 (0.021227135)	0.027754026 (0.036436931)	0.029694305 (0.027739460)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 2/5/1995-1/7/1997. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

Table 3.13: Long volume ratio results (Pre-crisis)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200
3.5									-0.049251731 (0.100882100)	-0.048647360 (0.086220300)	-0.049251458 (0.104352710)	-0.049251458 (0.104352710)
									-0.352561793 (0.165393068)**	-0.376202198 (0.112940024)***	-0.352555605 (0.184344484)*	-0.352555605 (0.184344484)*
3.0									-0.049251731 (0.100882100)	-0.048646857 (0.094901429)	-0.049251458 (0.104352710)	-0.049252009 (0.111106149)
									-0.352561793 (0.165393068)**	-0.376200903 (0.125053745)***	-0.352555605 (0.184344484)*	-0.352562967 (0.179117241)**
2.5	-0.107055077 (0.089956397)	-0.102257157 (0.080881432)	-0.107523646 (0.081418317)	-0.106558991 (0.078858181)	-0.083055356 (0.033518555)**	-0.082779068 (0.040358291)**	-0.081695517 (0.039271584)**	-0.082778931 (0.040908548)**	-0.068785051 (0.113462289)	-0.099853518 (0.092881926)	-0.087393399 (0.036659489)**	-0.059413935 (0.025645423)**
	0.008130263 (0.436500046)	-0.703912943 (0.511495492)	-0.122035349 (0.188800410)	-0.124522257 (0.645360068)	0.370932251 (0.149222766)**	0.354900901 (0.170417379)**	0.344366785 (0.127015308)***	0.354900312 (0.207213331)*	-0.119309067 (0.187970106)	0.039043290 (0.155263560)	-0.143340088 (0.153294376)	-0.004283014 (0.179346903)
2.0	-0.106398930 (0.079715886)	-0.108061907 (0.080483186)	-0.100929690 (0.054028540)*	-0.116663095 (0.048984604)**	-0.085191498 (0.038547949)**	-0.086644102 (0.037985452)**	-0.085117407 (0.031516670)***	-0.086644396 (0.037818432)**	-0.071602388 (0.206654708)	-0.094078073 (0.041067466)**	-0.095566190 (0.042910007)**	-0.081564481 (0.032927682)**
	0.037879998 (0.146941042)	-0.069662636 (0.081336515)	-0.110593634 (0.108463514)	0.097645007 (0.154006266)	0.138708094 (0.156001537)	0.191932687 (0.176156412)	0.077174697 (0.163952330)	0.191932318 (0.168311524)	-0.036730676 (0.101674262)	-0.049455278 (0.084622991)	0.002791917 (0.080795519)	0.000131897 (0.041669171)
1.5	-0.110812823 (0.082890487)	-0.105403982 (0.080370680)	-0.114270957 (0.076418880)	-0.092835942 (0.084343107)	-0.084953770 (0.041095201)**	-0.093023638 (0.042327974)**	-0.084945691 (0.041345537)**	-0.093808098 (0.039590850)**	-0.095514430 (0.046418107)**	-0.069687791 (0.090161716)	-0.092595625 (0.017102675)***	-0.084484866 (0.243243006)
	0.005888250 (0.064344102)	-0.002612866 (0.070906837)	0.011113874 (0.073079818)	-0.018935276 (0.073435423)	-0.000204203 (0.058312426)	0.054792526 (0.052575815)	-0.000803150 (0.055597820)	0.058104319 (0.049516199)	0.004784805 (0.061752597)	-0.040702014 (0.056575260)	0.000386780 (0.058649106)	-0.023764937 (0.077642908)
1.0	-0.077447933 (0.030762943)**	-0.046871592 (0.081713860)	-0.072572692 (0.034965160)**	-0.016170641 (0.088136472)	-0.091560462 (0.046501606)**	-0.094145019 (0.043426991)**	-0.079093808 (0.043470006)*	-0.093463404 (0.043221998)**	-0.045426714 (0.066113661)	-0.057739607 (0.068928037)	-0.084863354 (0.070506166)	-0.088248318 (0.075695252)
	-0.057840223 (0.077691324)	-0.072126128 (0.087939935)	-0.070079805 (0.112446556)	-0.110554740 (0.066916177)*	0.007428981 (0.034763808)	0.011900482 (0.039818598)	-0.010047421 (0.035425480)	0.010762029 (0.037681479)	-0.076298844 (0.042986601)*	-0.073841495 (0.047931133)	-0.053086036 (0.043330895)	-0.071366071 (0.045172222)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 2/5/1995-1/7/1997. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

3.7.4.b In-crisis: 2/7/1997-31/12/1998

The results for the feedback coefficient for Hong Kong and Taiwan for the in-crisis period are indicative of overt positive feedback trading (see Tables 3.14 and 3.15), which is found to be statistically significant in Hong Kong (5% level) and occasionally in Taiwan, for both short and long volume ratios; evidence of overt and statistically insignificant positive feedback trading can also be found in South Korea, yet only for short volume ratios⁶⁵.

Results for the threshold coefficient from tests with short volume ratios during the crisis indicate a rather mixed picture for Hong Kong, with the threshold coefficient failing to align itself with any distinctive feedback direction; statistical significance appears to be sporadic. Similar results were obtained when long volume ratios were tested. However, there, we managed to observe something rather interesting at rank 1.0, as all four volume ratios there exhibited a uniform, statistically significant (1% level) positive feedback trading pattern. Since no statistical significance was encountered for the threshold coefficient at rank 1.5 for three (VR150, EVR150, EVR200) out of those four volume ratios, we ran further tests using the area between ranks 1.0 and 1.5 as a threshold; results revealed that the significance of the threshold coefficient documented above persisted within the area between ranks 1.0 and 1.5 for all four volume ratios.

Regarding South Korea, the threshold coefficient is found to be nearly always⁶⁶ indicative of overt (and mostly statistically insignificant) positive feedback trading when we test for short volume ratios. Tests with long volume

⁶⁵ Results from long volume ratios for this coefficient in South Korea contain evidence of both positive as well as negative feedback trading.

⁶⁶ With the exception of the threshold coefficient at ranks 1.0.(VR20, VR150, EVR150, EVR200).

ratios failed to reveal any distinctive threshold direction; significance there appeared to be mostly concentrated in the top ranks (3.0 and above)⁶⁷.

Results from short volume ratio tests for Taiwan generated a rather mixed picture, with the threshold coefficient failing to align itself with any distinctive trading direction, while results from long volume ratio tests contained evidence of overt positive feedback trading⁶⁸; statistical significance (5% level) here tends to manifest itself mostly at rank 1.5 and is indicative of positive feedback trading.

3.7.4.c Post-crisis: 1/1/1999-31/12/2003

The results for the feedback coefficient for all three markets for the post-crisis period are indicative of overt positive feedback trading (see Tables 3.16 and 3.17), which is found to be statistically significant for Hong Kong (5% level) for both short and long volume ratios; the cases of South Korea and Taiwan provide us with evidence of scattered statistical significance (10% level) for both short and long volume ratios.

When short volume ratios were used, the results for the threshold coefficient for Hong Kong after the crisis indicated a rather mixed picture, with the threshold coefficient failing to align itself with any distinctive feedback direction; statistical significance appeared to be sporadic. Notably though, a statistically significant (10% level), negative feedback trading pattern appeared during the post-crisis period at rank 1.0 (see Table 3.16).

⁶⁷ *At those ranks, threshold traders appeared to adhere exclusively to positive feedback trading.*

⁶⁸ *With the exception of the threshold coefficient of the VR150 at rank 2.0.*

Table 3.14: Short volume ratio results (In-crisis)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20
2.0	-0.014472596 (0.006705961)**		-0.013623572 (0.006175529)**	-0.014460422 (0.006180284)**			-0.002697493 (0.005581637)				-0.033367737 (0.043117905)	
	0.255643478 (0.233519514)		-0.017674522 (0.060823352)	0.263150183 (0.161346878)			-0.095161173 (0.022536434)***				0.383852108 (0.473018827)	
1.5	-0.014677137 (0.005785461)**	-0.013291989 (0.003780643)***	-0.012949420 (0.006031616)**	-0.013828369 (0.006144092)**	-0.003797352 (0.006839434)	-0.004000823 (0.005238623)	-0.002347915 (0.006703401)	-0.002543910 (0.005474987)	-0.037810372 (0.012262663)***	-0.030593445 (0.029713276)	-0.032780018 (0.048939544)	-0.033394134 (0.025239001)
	0.002184009 (0.013428354)	-0.011707369 (0.009897559)	-0.014824208 (0.008548524)*	-0.012744391 (0.020727958)	-0.002405392 (0.018215529)	-0.013338764 (0.024786482)	-0.008610086 (0.006937248)	-0.019698084 (0.015810130)	0.100795060 (0.157111878)	0.077661378 (0.069856824)	-0.005846067 (0.079834672)	0.103598014 (0.075043258)
1.0	-0.021079793 (0.006431002)***	-0.020348852 (0.006460359)***	-0.020945871 (0.007701497)***	-0.013156601 (0.004634209)***	-0.001613105 (0.008552286)	-0.001317835 (0.006517591)	-0.006404516 (0.009869022)	-0.002476857 (0.008956022)	-0.007348966 (0.031926057)	-0.015061372 (0.039014662)	-0.033757271 (0.042305255)	-0.036319206 (0.033038766)
	0.008680858 (0.006065825)	0.007728187 (0.006073299)	0.008333104 (0.006601609)	-0.004547882 (0.006204008)	-0.002776652 (0.005238744)	-0.003110406 (0.004834916)	0.003482548 (0.006874381)	-0.001918710 (0.006158317)	-0.037869119 (0.042766240)	-0.022991370 (0.053880961)	0.000421035 (0.028618741)	0.004186310 (0.045016428)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 2/7/1997-31/12/1998. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

Table 3.15: Long volume ratio results (In-crisis)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200
3.5							-0.003466786 (0.006944225)					
							-0.021676090 (0.013176223)*					
3.0			-0.014247793 (0.005764719)**		-0.003427253 (0.008233850)	-0.002441583 (0.006223304)	-0.002252077 (0.002370165)	-0.003172787 (0.006991832)				
			0.034145413 (0.093627712)		-0.032406868 (0.017021110)*	-0.095399320 (0.011902273)***	-0.011009763 (0.009854507)	-0.031980485 (0.015414882)**				
2.5	-0.014250888 (0.006161437)**	-0.014154851 (0.005796549)**	-0.013296587 (0.005393306)**	-0.014103864 (0.006385298)**	-0.002082302 (0.003096997)	-0.002656179 (0.006438976)	-0.001982276 (0.007177922)	-0.002728510 (0.006267884)				
	0.023755830 (0.095803972)	0.034893667 (0.085855027)	0.149351505 (0.052260029)***	0.036113894 (0.072363834)	-0.007766882 (0.007763398)	-0.003785529 (0.010766779)	-0.006793310 (0.010265487)	-0.003230592 (0.010031254)				
2.0	-0.013893887 (0.006174488)**	-0.013865146 (0.005846505)**	-0.014315253 (0.006392528)**	-0.014258887 (0.005531486)***	-0.002335925 (0.007479211)	-0.003609983 (0.001357498)***	-0.001107153 (0.007411699)	-0.002524355 (0.007015439)	-0.033453690 (0.060333672)			
	0.064920629 (0.073236703)	0.077505544 (0.089082803)	0.011189856 (0.046773247)	0.017708600 (0.088580423)	-0.002098234 (0.007192693)	-0.000753384 (0.003685964)	-0.003715281 (0.007521371)	-0.001759288 (0.007917755)	0.127141117 (0.106387105)			
1.5	-0.015208413 (0.005965501)**	-0.013712391 (0.005702424)**	-0.014134992 (0.006220580)**	-0.014857619 (0.005437743)***	-0.001780596 (0.002303828)	0.004459369 (0.009731808)	0.002079089 (0.004112589)	0.004590839 (0.009670484)	-0.030976988 (0.035422909)	-0.028979615 (0.034000046)	-0.032906747 (0.034110515)	-0.030769856 (0.031370920)
	-0.023761708 (0.015582980)	0.029854132 (0.058075883)	-0.029638773 (0.013983154)**	-0.021963946 (0.013446549)	-0.002319511 (0.002721312)	-0.008598622 (0.006599149)	-0.005584869 (0.004343028)	-0.008794338 (0.006369000)	-0.125611509 (0.060302558)**	-0.147413069 (0.058542916)**	-0.111409952 (0.076452589)	-0.134265667 (0.054735235)**
1.0	-0.015243246 (0.005815423)***	-0.013681562 (0.005725846)**	-0.013668166 (0.005000531)***	-0.013576698 (0.005962453)**	-0.009457152 (0.012845324)	-0.010681321 (0.011356847)	0.003295384 (0.011300902)	-0.008281773 (0.013832795)	-0.031897550 (0.051887118)	-0.028500890 (0.034977841)	-0.032619326 (0.040145624)	-0.029316661 (0.039564608)
	-0.031269314 (0.012074331)***	-0.035057401 (0.005033132)***	-0.034459270 (0.006614643)***	-0.034528471 (0.011066263)***	0.005748162 (0.009095254)	0.006720132 (0.008049129)	-0.007465690 (0.008393210)	0.004521142 (0.009901497)	-0.018081288 (0.071815551)	-0.016860853 (0.028691325)	-0.060820341 (0.040719838)	-0.010548400 (0.035000041)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 1/7/1997-31/12/1998. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

Further tests for that period revealed that this pattern's significance is encountered (10% level) within the area between ranks 1.0 and 1.5. When long volume ratios were used, results were overtly indicative of negative feedback trading of circumstantial statistical significance.

When short volume ratios were used, the results for South Korea during the post-crisis period were nearly always⁶⁹ indicative of positive feedback trading on behalf of threshold traders; statistical significance was absent here. The results from the tests with long volume ratios indicated a rather mixed picture, with the threshold coefficient failing to align itself with any distinctive feedback direction; its statistical significance exhibited signs of clustering at the top ranks of each long volume ratio, where the threshold sign was indicative of a statistically significant, positive feedback trading pattern.

Tests with both short and long volume ratios after the crisis generated a rather mixed picture for Taiwan, with the threshold coefficient failing to align itself with any distinctive feedback direction. The statistical significance of the threshold coefficient here tends to manifest itself mostly at the top ranks of the long volume ratios only; more specifically, at ranks 3.0 and above the indication (much like for the in-crisis period) is one of statistically significant (10% level) positive feedback trading⁷⁰.



⁶⁹ With the exception of the threshold coefficient of the VR20 at ranks 1.0. (in-crisis) and 1.5 (post-crisis).

⁷⁰ With the exception of the top rank (2.5) of the EVR200, which gave us a threshold coefficient indicative of negative feedback trading.

With regards to the presentation of the results above, we may note the following. First of all, it is interesting to note that, with the exception of a limited number of tests, the feedback coefficient appears to be firmly tilted towards positive feedback trading irrespective of the period under investigation (pre-, in- or post-crisis). The temporal presence of its statistical significance does not exhibit uniformity across the three markets; in Hong Kong it manifests itself significantly during and after the crisis, in South Korea before and after the crisis, while it does not appear to be overwhelmingly significant in Taiwan in any of the three sub-periods. None of the three markets furnished us with evidence of any discernible significant threshold pattern, be it for short or long volume ratios for the in-crisis period; as a result, we fail to accept the fifth hypothesis here for any of them.

3.8 Conclusion

Exploiting noise traders is not necessarily a practice confined to rational, fundamentals-based investors; even investors without explicit knowledge of fundamentals may try to exploit the trading conduct of noise traders. A number of analytical models have been proposed in the Finance literature to describe both “modes” of exploitation. Contrary to fundamentals-based speculation, however, the concept of non-fundamental speculation has never been tested empirically, i.e. using real-market data.

Table 3.16: Short volume ratio results (Post-crisis)

	Hong Kong				South Korea				Taiwan			
RANKS	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20	VR10	EVR10	VR20	EVR20
2.0	-0.052478322 (0.021028180)**		-0.051115617 (0.022744499)**				-0.024983106 (0.030492564)				-0.018557919 (0.010820416)*	
	-0.000739192 (0.084143328)		0.170493694 (0.289039947)				-0.011280933 (0.278094671)				-0.081826776 (0.051606075)	
1.5	-0.054134026 (0.020236527)***	-0.052466856 (0.018644219)***	-0.059091163 (0.019400391)***	-0.051410439 (0.016892770)***	-0.024561619 (0.008673483)***	-0.025118518 (0.011479538)**	-0.025466605 (0.010067067)**	-0.025426022 (0.013312368)*	-0.019395170 (0.011187718)*	-0.019182775 (0.012199009)	-0.018652681 (0.010961245)*	-0.018667924 (0.009877218)*
	0.061085114 (0.058403685)	-0.001439448 (0.091610743)	0.029161907 (0.040317659)	-0.021688292 (0.039337573)	-0.013641915 (0.017990788)	-0.017761050 (0.029866102)	0.001137778 (0.013704319)	-0.010949738 (0.022821404)	0.041372560 (0.025902259)	0.070955256 (0.052211330)	-0.000502141 (0.021509905)	0.014879699 (0.022455485)
1.0	-0.079360824 (0.021668441)***	-0.071233818 (0.022176005)***	-0.056247322 (0.017543873)***	-0.062477767 (0.013805034)***	-0.022467433 (0.039674729)	-0.021948597 (0.013713642)	-0.012330752 (0.009815951)	-0.012846004 (0.012447303)	-0.020184740 (0.009207081)**	-0.018514657 (0.010358259)*	-0.013389424 (0.004460240)***	-0.015791668 (0.013271470)
	0.036480483 (0.019251905)*	0.029201108 (0.015393116)*	0.012112191 (0.018574968)	0.031571534 (0.012874723)**	-0.004061380 (0.006596280)	-0.005580548 (0.007504293)	-0.015548101 (0.007254841)**	-0.013735601 (0.008834937)	0.003401035 (0.010576949)	-0.000436361 (0.012918109)	-0.013852161 (0.014205609)	-0.007006851 (0.013345514)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 1/1/1999-31/12/2003. (= 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).*

Table 3.17: Long volume ratio results (Post-crisis)

	Hong Kong				South Korea				Taiwan			
RANKS ↓	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200	VR150	EVR150	VR200	EVR200
3.5			-0.052868882 (0.020384993)***									
			0.261798115 (0.263912037)									
3.0	-0.057570867 (0.020664115)***		-0.052842412 (0.019811284)***	-0.054329365 (0.018587425)***	-0.025579440 (0.009257614)***		-0.025309227 (0.008032146)***	-0.024723580 (0.011927500)**	-0.018600922 (0.009787545)*		-0.018659107 (0.011524018)	
	0.198795630 (0.169312140)		0.008303240 (0.061726523)	0.037117757 (0.070642069)	-0.133422522 (0.012124532)***		-0.009867999 (0.148170336)	-0.134611996 (0.013190287)***	-0.121999244 (0.038253626)***		-0.142188213 (0.026942429)***	
2.5	-0.060055296 (0.013837316)***	-0.053741012 (0.023314811)**	-0.058860393 (0.018126429)***	-0.058785659 (0.017359169)***	-0.024554420 (0.010931065)**	-0.024081778 (0.008097438)***	-0.025416013 (0.012651693)**	-0.024673581 (0.022329525)	-0.018553931 (0.011109998)*	-0.018601061 (0.011354040)	-0.018357170 (0.012082139)	-0.018061964 (0.011567825)
	0.065640103 (0.026650550)**	0.030465519 (0.017264840)*	0.055644577 (0.041699516)	0.059886585 (0.061675250)	-0.020438869 (0.043198438)	-0.057967054 (0.020238944)***	-0.029989329 (0.025671855)	-0.015209843 (0.035679883)	0.016692174 (0.071448145)	-0.121976481 (0.044295028)***	0.037026300 (0.071570101)	0.168664308 (0.066756562)**
2.0	-0.059892565 (0.018240443)***	-0.059066659 (0.019498216)***	-0.058111344 (0.018156982)***	-0.059055609 (0.018867787)***	-0.025331815 (0.012870235)**	-0.023167900 (0.012146432)*	-0.022766655 (0.014092186)	-0.025217244 (0.007562194)***	-0.018639829 (0.012417598)	-0.018695730 (0.011093014)*	-0.018478656 (0.012479702)	-0.018696100 (0.012499924)
	0.067857755 (0.043884614)	0.054063586 (0.044716042)	0.057662134 (0.042473286)	0.055520334 (0.043945106)	0.005709600 (0.022984156)	-0.011566917 (0.022311147)	-0.015870035 (0.015281148)	-0.008033805 (0.014448544)	0.002637714 (0.035651834)	-0.003246471 (0.051402261)	0.007271074 (0.045473008)	-0.002374040 (0.051011443)
1.5	-0.056636230 (0.014239695)***	-0.057644144 (0.016317209)***	-0.055089735 (0.116808606)	-0.057558051 (0.016057980)***	-0.026780025 (0.013750859)*	-0.025889314 (0.013256228)*	-0.027486073 (0.011450757)**	-0.024946813 (0.011837901)**	-0.018596757 (0.010908002)*	-0.019778172 (0.009571448)**	-0.018897713 (0.012251939)	-0.020485840 (0.012365291)*
	0.043843983 (0.029300071)	0.043026529 (0.039052463)	0.035346251 (0.032678458)	0.043060809 (0.036725891)	0.007106681 (0.011173258)	0.003824567 (0.012807112)	0.009996532 (0.008810185)	-0.001378595 (0.009932280)	-0.015309048 (0.018028748)	-0.018307626 (0.022075892)	-0.004841232 (0.017465963)	-0.026226657 (0.024700993)
1.0	-0.053659410 (0.015391600)***	-0.054368641 (0.018520479)***	-0.055465272 (0.019555131)***	-0.054936626 (0.019845857)***	-0.021819116 (0.011921716)*	-0.011576640 (0.014382247)	-0.023103234 (0.011196254)**	-0.021472978 (0.007937633)***	-0.021646575 (0.010433572)**	-0.022214046 (0.011719682)*	-0.018241726 (0.012330706)	-0.019616339 (0.003980333)***
	0.012335929 (0.012384391)	0.015698971 (0.022338313)	0.032404613 (0.007250245)***	0.019525564 (0.019153557)	-0.007294730 (0.005985294)	-0.013957895 (0.008701657)	-0.003748610 (0.004263577)	-0.005074802 (0.004758987)	0.012956136 (0.012261320)	0.013738258 (0.010459530)	-0.004575313 (0.011717031)	0.006055232 (0.007822154)

White rows indicate the results for the feedback coefficient, while the shaded rows correspond to the threshold coefficient. Parentheses include the standard errors of the estimates; sample period: 1/1/1999-31/12/2003. (* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level).

To address this issue, we introduced a novel trader-type (“threshold trader”) who is not a “fundamentalist”, yet conditions his trades upon a certain piece of information that allows him insight into the underlying market trend (and, through the latter, into the presence of noise traders, portrayed here as feedback traders). We assumed that the “threshold trader” uses a technical indicator (volume-ratio) and becomes active anytime its value exceeds a certain threshold reflecting a rise in volume. To test for the presence of threshold traders empirically, we used a modified version of the Sentana and Wadhwani (1992) model for various values, lengths and specifications of the volume-ratio.

We tested for the significance of the presence of threshold traders in three markets (Hong Kong, South Korea, Taiwan), because our intention was to study how the threshold-traders’ behaviour manifested itself in markets with differences in the regulatory settings related to the entry/trading conduct of investors, i.e. with differences in their degree of financial liberalization; the degree of market-heterogeneity (reflected here through the participation of foreign investors) was introduced here as an indicator of a market’s liberalization.

Results indicated a discernible and statistically significant threshold trading pattern in the Hong Kong market when short volume-ratios were used, and we showed how that market’s regulatory environment, coupled with its heterogeneity could be employed as possible factors to account for this pattern. The latter maintained its discernibility during the period prior to the rise in overseas investors’ participation; however, when comparing its presence at those ranks at which it was found to be significant in the period prior to the rise in foreign trading to the same ranks for the period following this rise, it was found to be insignificantly different. South Korea and Taiwan generated no statistically

significant, discernible threshold patterns, be it for the full period or for the sub-periods associated with our heterogeneity-related hypothesis.

We also tested for the threshold traders' presence during the 1997 Asian crisis period, in line with the widely documented positive volatility-volume relationship (Karpoff, 1987), since rising volume was designated to be their trading basis; none of the three markets was found to demonstrate significantly discernible threshold patterns during the Asian crisis period.

Our evidence suggests that the degree of a market's heterogeneity (i.e. the participation of overseas investors) does appear to be conducive to the rise of certain threshold trading patterns; our results, actually, imply that a liberal regulatory environment and higher foreign participation tend to favour the manifestation of threshold trading patterns⁷¹. Since threshold traders operate under a feedback demand function, this is in line with what we mentioned in the beginning (Section 3.5) regarding the practice of feedback trading and how it may vary across different regulatory regimes.

We would like to accentuate the fact that our study constitutes an initial attempt to test for non-fundamental speculation empirically. It is our understanding that the choice of the indicator upon which threshold traders would trade is only limited by the availability of indicators (and relevant data). We reckon that further studies on the issue of threshold trading could involve other (volume- and non-volume-based) indicators to test for the behaviour of threshold

⁷¹ *The wording here may appear cautious, however, we consider it appropriate to repeat here that our results provided us with indications "in favour" of the heterogeneity-hypothesis for a specific category (short) of volume ratios; long volume ratios did not provide us with similar results in the case of Hong Kong. As a result, claiming that Hong Kong's heterogeneity leads to threshold traders being able to demonstrate any discernible pattern would probably be inaccurate here.*

traders, as well as other proxies (beyond heterogeneity) to account for their possible patterns.

Chapter 4

An Investigation of the Impact of Specific Regulatory Provisions upon Market-wide Herding

4.1 Introduction

Herd behaviour has received notable attention in the Finance literature during the last two decades to the extent that it has led to the evolution of a rather impressive research strand. A large array of studies, both *analytical* as well as *empirical* in nature (Bikhchandani and Sharma, 2001; Hirshleifer and Teoh, 2003) have attempted to provide extra insight into various aspects of the herd mentality. *Analytical* models have attempted to illustrate various possible theoretical manifestations of herding, often by invoking the concept of informational cascades as a result of social interactions (e.g. Banerjee, 1992; Bikhchandani et al, 1992) and professional considerations (e.g. Scharfstein and Stein, 1990; Trueman, 1994). *Empirical* studies have endeavoured to quantify herding, either through the employment of microdata⁷² (e.g. Lakonishok et al, 1992; Wermers, 1999) or aggregate data (e.g. Christie and Huang, 1995; Chang et al, 2000; Hwang and Salmon, 2004); research of the kind has been quite extensive, the result being that

⁷² The term “microdata”, when used in our chapter, shall refer to any type of data related to investment entities, be they of individual, institutional or other background; it covers data, such as investors’ accounts and transaction-data. We make use of the term as opposed to “aggregate” data, which refer to any type of data related to the aggregate market level, such as prices, volume et al.

empirical evidence regarding herding is now available for various markets internationally.

An interesting feature of the empirical research relative to herding is that it has mostly been carried out within the contexts of single markets, with the aim of assessing herding, either across specific investor-types (e.g. Lakonishok et al, 1992; Wermers, 1999; Choe et al, 1999; Kim and Wei, 2002a and b) or across various market segments (Christie and Huang, 1995; Gleason et al, 2004, Demirer and Kutan (2006) or both (Oehler, 1998). Exceptions to the above constitute the studies by Chang et al (2000) and Hwang and Salmon (2004) who study herding across a variety of markets. However, the choice of those markets in these studies is not motivated by the existence of certain features of theirs that could potentially bear an effect upon herding but rather hinges upon a simple comparison of “developed versus developing markets”. As a result, there appears to be a scarcity of empirical herding research both at the comparative level (i.e. examining herding in different markets) as well as with regards to the relation of specific market features to herding.

To that end, we extend the scope of empirical research in this area by testing for herding on an inter-market basis conditional upon factors that have the potential of bearing an impact upon the observed herding; more specifically, we test for herding on the basis of the following features: a) capital gains’ taxes, b) short-sales’ restrictions and c) index-futures’ introduction. The first feature hinges upon the notion that the presence/absence of capital gains’ taxes may influence herding in the marketplace. The second feature is based upon the concept (Miller, 1977) that short-sales’ restrictions can give rise to overpricing; as overpricing is a possible byproduct of herding, the latter’s significance may well be amplified in

the presence of such restrictions. Finally, the third feature is based upon the association between herding and positive feedback trading and recent (Antoniou et al, 2005b) empirical evidence according to which the introduction of index-futures bears an effect over the positive feedback trading at the underlying spot market's level. All in all, our aim here is to test whether the aforementioned three features promote or inhibit the manifestation of herd behaviour across markets.

A key distinguishing feature of our research relates to the fact that our study is not driven by an abstract notion of testing for herding in any single market or across *any* randomly chosen markets; rather it is the array of herd-related market-features that motivates the choice of our sample. In addition to that, it allows for extra insight into the implications of specific regulatory provisions, as the features upon which the significance of herding is tested constitute elements of the capital market regulatory framework.

The rest of the chapter is organized as follows: Section 4.2 includes a review of the literature pertaining to herd behaviour (4.2.1) with special reference to the features (4.2.2) we are testing for with regards to herding. Section 4.3 presents the entire model-development of our concept while Section 4.4 delineates the hypotheses relative to our study. Section 4.5 presents the data utilized (4.5.1) discusses the methodology employed (4.5.2) and presents some descriptive statistics (4.5.3). Section 4.6 presents the results and discusses the empirical findings; Section 4.7 concludes.

4.2 Theoretical Background

4.2.1 Definitions and Sources of herding

Herding, as Hirshleifer and Teoh (2003) have noted, involves a “similarity in behaviour” following “interactive observation”. Therefore, herding is witnessed when people follow the observable information, actions or the payoffs from those actions of others. However, the rationale underlying this tendency towards imitating others is not easy to delineate, as it appears to be ascribed to various motives, which we shall now discuss.

i) *Psychology*: In line with popular beliefs, the impetus underlying imitation has been assumed to lie within the human nature: people may simply prefer to copy others. This tendency towards conformity (Hirshleifer, 2001)) may well be related to the interaction of people, as they communicate with one another. Communication may be explicit (e.g. when people are conversing - see Shiller, 1995), yet it may also be tacit (when people observe each others’ choices, e.g. in fashion – see Bikhchandani et al, 1992). Thus, it is the very fact that humans dwell within societies and the concomitant interactions among them due to this cohabitation that lay the ground for the evolution of imitative phenomena.

ii) *Payoff externalities* (Devenow and Welch, 1996): Following the decisions of others may be associated with informational payoffs, when one: a) possesses no private information, b) has private information yet is uncertain about it, perhaps because it is of ambiguous or low quality. c) perceives others as better-informed or d) perceives his abilities of processing information to be inadequate. If so, he may choose to free-ride on the informational content of others’ actions,

thus tackling the problem of information-acquisition (and the relevant uncertainty).

iii) *Informational cascades*: If an investor possesses private information, he may still decide to ignore it and follow the actions of others, when the information conveyed by others' actions provides a useful set of information on its own (Bikhchandani and Sharma, 2001). This is expected to be particularly the case when the alternative options available are limited; if the latter holds, then this will translate into an equally limited array of possible responses towards those options, thus enhancing the potential for converging to one of them (Devenow and Welch, 1996).

iv) *Professional reasons*: Professionals, be they fund managers or analysts are subject to periodic evaluation (Scharfstein and Stein, 1990) which is normally of a relative nature, i.e. they are evaluated on the basis of the performance of their peers, mostly those with similar (e.g. stocks, bonds, money-market, industry, foreign market/s et al) specializations (Ross et al, 1999). Since their abilities do not exhibit uniformity, this provides them with an incentive to monitor the trades of their peers in order to avoid deviating from the perceived "benchmark" (Lakonishok et al, 1992).

Such a situation, where separating "luck" from "skill" has important career implications is depicted by Scharfstein and Stein (1990), who posit that in an environment characterized by some kind of uncertainty, it might pay off for professionals to imitate their peers' actions and ignore their private information when making decisions. Assuming that positive circumstances materialize in the market, highly skilled ("good") managers will make successful decisions while less skilled ("bad") ones will presumably be inclined to "herd" on those, so that

everyone gives the impression of being equally “skilled”. Conversely, if adverse circumstances materialize, it is hard to tell who is “good” (the “bad” ones will have performed “badly” anyway, while the “good” ones will have probably performed worse than expected).

v) *Reputational considerations*”: Well-reputed managers may opt for herding if reputational fears prevail (i.e. if the potential damage to their reputation by a failure outweighs the expected benefits from a success); less-reputed managers may resort to herding as a means of free-riding on the reputation of better-reputed colleagues. If we assume that the well-reputed individuals are also the better-able ones (as it is hard to imagine how a manager’s reputation would have grown in the absence of a distinctive ability), this may help explain the herding tendencies denoted previously with regards to the issue of ability. A number of studies (Trueman, 1994; Graham, 1999) conducted within the field of financial analysts have shown how the expectation of reputational externalities can lead to herding. Trueman (1994) shows that under conditions of uncertainty, it is convenient for a “weak” analyst to behave as if he were “strong” through copying his “stronger” peers, since he stands a fair chance of gaining the investors’ recognition (*reputational externality*), as soon as the information of his “strong” peers proves correct. Graham (1999) shows that, when an analyst’s remuneration is associated with his reputation, a well-paid analyst would opt for herding, if that would help him maintain his high reputation - and salary.

vi) *“Homogeneity”*: The argument here pertains mostly to investment professionals (fund managers, financial analysts) and hinges around a few simple facts (Lakonishok et al, 1992; De Bondt and Teh, 1997; Wermers, 1999). These professionals constitute a group of more or less similar traits: they share similar

educational backgrounds and qualifications, are exposed to similar information signals, may tend towards interpreting them similarly (due to background-similarities or peer-mimicking) and are subject to a similar framework of professional conduct (e.g. compensation schemes, notions of prudence and fiduciary duty (De Bondt and Teh, 1997). As a result, it is reasonable to assume that their group entails a certain degree of homogeneity, which in turn may well render them prone to commonalities in their decision-making, like for instance maintaining similar structures of their portfolio-holdings (the case of fund managers selecting stocks picked up by many of their peers-see Lakonishok et al, 1992) or adhering to the line of the “opinion leaders” or the perceived majority (as may well be the case with financial analysts-see, e.g. Graham, 1999 and Welch, 2000).

vii) *Spurious herding*: According to Bikhchandani and Sharma (2001), this involves a similarity of responses to commonly observed signals. An example here involves the case of changes in fundamentals becoming public knowledge as they have the potential of inducing people to behave in a parallel fashion; a drop in deposit rates, for example may lead investors to turn to the stock market in search for higher returns.

viii) *Manipulative intent*: The actions of a group of informed traders may create the impression of a profitable opportunity, thus luring others into it (Van Bommel, 2003). The positive feedback mechanism involved in such cases may well lead to the manifestation of herding phenomena, where individuals engage in interactive trend-chasing. The possibility of rational speculators launching the latter has been established in several analytical studies (De Long et al, 1990; Andergassen, 2003) as well as empirically (Soros, 1987).

Thus, as our presentation so far suggests, herding is a phenomenon of a rather versatile nature and multifaceted manifestations. We shall now attempt to delineate the role of the features upon which our investigation of herding will take place.

4.2.2 Herding and relevant market features

In this section, we will present the case of the association between herding and certain market features that have the potential of bearing an impact upon it. These features refer to provisions of the capital markets' regulatory framework and include capital gains' taxes, short-sales' constraints and index-futures.

4.2.2.a Capital gains' taxation

Prior to embarking on the discussion of the relationship between herding and capital gains' taxes, we consider it necessary to note from early on that this issue: a) has never been investigated before and b) as such has not been resolved. Our discussion here shall aim at delineating the theoretical context of the topic.

We first present the case of the *presence* of capital gains' taxes bearing a positive impact upon herding. If capital gains' taxes are present, this implies that the realization of any profits through the liquidation of positions is bound to come at a cost. Given that other costs are also involved in the trading process (e.g. brokerage fees), such taxes are expected to raise transaction-costs, thus rendering the market more frictional. If so, then there exists the potential for an impact upon the valuation of assets, the direction of which has evoked considerable debate in Finance. In their recent review on this issue, Dai et al (2006) outline the two

possible effects of capital gains' taxation discussed in the relevant literature, namely the *capitalization-effect* and the *lock-in effect*. In the presence of capital gains' taxes, the former implies that investors prefer to buy stocks at a lower price while the latter argues that they would prefer to sell at a higher price.

We, therefore, notice that capital gains' taxes are capable of bearing a certain impact upon the behaviour of investors, thus raising concerns about the efficiency of the price-formation process (Ho et al, 2002). If investors' gains are subject to taxation, then this probably means that the frequency of their trades will be reduced. Indeed, the higher the level of capital gains' taxes, the less inclined investors would be to engage in "aggressive" trading, as the accrued profits from frequent transactions would be adversely affected by taxation, especially in jurisdictions where capital gains' taxes are a function of the stock-holding period. If however, capital gains' taxes provide a disincentive for intensive trading this may also be taken to imply that they tend to cast a negative effect upon market activity. It follows, that traders, who for some reason, wish to buy and sell at a short window may be partly discouraged from doing so, the latter indicating that their information (as imprinted in their trades) will not enter the public information pool-and hence, will not be imprinted into stock prices. As a result, a situation of the kind is expected to produce some negative impact upon efficient pricing (Ho et al, 2002).

Given that capital gains' taxes affect the sell-side of the market, the latter will appear less "expressive" than the buy-side, hence facilitating phenomena of upwards mispricing (overpricing). Since herding is capable of generating overpricing (e.g. during price-rallies), it is reasonable to assume that the presence of capital gains' taxes is a factor contributing to the manifestation of herding;

having said that, however, we by no means wish to imply that it constitutes a cause of it.

We shall now present the case of the *absence* of capital gains' taxes impacting positively upon herding. Assuming complete absence of capital gains' taxes, this would provide traders with an incentive to trade more "intensely". If an investor does not have to pay tax on the gains he realized from the liquidation of his positions, he may well choose to trade (buy and sell) more aggressively. If the latter is associated with information-based trading, then obviously this benefits market prices from an efficiency point of view. However, if speculative considerations prevail (e.g. there exists widespread day-trading), then this may lead to mispricing, in case the higher intensity of trades leads to larger price-swings. The "*overconfidence*" bias would be expected to be rather relevant in this context, since, as Odean (1998) and Glaeser and Weber (2004a; 2004b) have shown, overconfidence tends to be associated with a higher frequency of trading. Thus, in such a situation, investors might be more inclined towards "gambling-to-win", as the realization of their profits would come at a reduced cost (compared to a market that taxes capital gains). Also, if the absence of capital gains' taxes renders trading less costly, it may also lead more traders to enter the market. This alone bears the potential of inducing herding, as the latter is primarily the byproduct of a participative process (e.g. Bikhchandani et al, 1992). However, higher investors' participation need not necessarily be herd-inducing, if it results in the impounding of more information in the marketplace, since this will actually lead to more efficient pricing.

The case of herding being tacitly promoted through the absence of capital gains' taxation is presented in a different context by Kim and Wei (2002a), who

tested for the role of overseas institutional traders in the Korean market between December 1996 and December 1999; their tests involved examining the intensity of trading, as well as herding and positive feedback trading on behalf of various onshore and offshore foreign funds before, during and after the Asian crisis period. Utilizing a unique micro-database, they showed that offshore funds as well as funds from Hong Kong and Singapore tended to trade more aggressively, yet also engaged in less herding and positive feedback trading when compared to their counterparts from the US and Europe. This “aggression” in their trading patterns was interpreted by the authors as a result of the fact that offshore jurisdictions (as well as the Hong Kong and Singapore ones) do not impose any taxes on the capital gains realized by funds registered with them; conversely, the US and the European jurisdictions do levy their funds with taxes on the basis of their capital gains. However, what Kim and Wei (2002a) postulate is that it is the tax-environment of the foreign funds’ countries that impacts upon their herding propensity in the host market (in their case, Korea); our intention here is to examine how the tax environment of the host market affects such herding considerations.

Thus, the relationship between herding and capital gains’ taxes remains, at best, an unresolved issue, with arguments pointing towards a versatile relationship. Given the above discussion, we propose testing for the hypothesis of *a significantly different manifestation of herding between markets with and without capital gains’ taxes.*

4.2.2.b Short-selling

The notion of short-selling is that someone sells a stock he does not own at present with the obligation of buying it back at a future price. The idea here is that the future price is anticipated to be below the price at which he sold “today” (i.e. the day the sale was formalized) otherwise there would be little incentive to engage in such a transaction (Mathiopoulos, 2000).

Miller (1977) and Baker and Stein (2004) show that short-sales’ restrictions have the potential of leading to price-overvaluation. According to them, a capital market is bound to accommodate people of heterogeneous beliefs; to simplify things, let us assume that the two major forces in the marketplace are those who are positively predisposed towards a stock (“optimists”) and those who are negatively predisposed (“pessimists”). It is also reasonable to contend here that the former will probably be on the buy-side of the stock while the latter on its sell-side. If short-sales’ restrictions were to apply, this would imply that the sell-side of the market would be deprived of a trading tool; as a result, the buy-side would tend to appear stronger. A strong buy-side would, consequently imply that the possibility of mispricing cannot be ruled out, as part of the sell-side (those who do not own the stock) is unable to express itself. If the buyers can have a greater impact, then the latter might be imprinted in prices, leading them perhaps to deviate from fundamentals, i.e. to overpricing. Miller’s picturing of this relates to a “demand-and-supply” notion. Short-sales’ restrictions would lead to a less elastic sell-side (supply), as the latter would incorporate only those holding the stock (short-sellers would be proscribed from trading); as a result, the market would face an upward price-pressure from a stronger demand (buy-side).

How this can be associated with herding is not hard to imagine. If at some point in time the price of a stock rises above fundamentals due to the prevalence of herd-instincts and there is no possibility of short-selling, those who may have expected this and would have otherwise sold the stock short on beforehand are unable to do so now. This means that the overpricing can persist for longer, as the sell-side is not strong enough to counter it. As a result, short-sales' restrictions may amplify the potential impact of herding (assuming the latter is at work) over the upwards mispricing of stocks.

Given our discussion thus far, we test for the hypothesis of *the introduction of short-sales leading to a reduction of herding in the marketplace*.

4.2.2.c Index-futures' introduction

In the seminal study on this issue, Antoniou et al (2005b) documented a reduction in the significance of positive feedback trading of the underlying spot markets across major stock exchanges following the introduction of index-futures. The authors justify their findings by invoking the assumption that index-futures are able to promote informational efficiency in the marketplace by attracting more informed (rational) players.

The choice of the introduction of index-futures in our research as a market-feature capable of affecting herding is based upon conceptual considerations related to the association between herding and positive feedback trading. In its simplest form, positive feedback trading implies trading in the direction of the perceived trend: buy when prices rise, sell when they fall. Thus, positive feedback trading can be described as *trend-based*. On the other hand, herding implicitly assumes the interactive observation (Hirshleifer and Teoh,

2003) among individuals, based upon which they follow each other. However, if imitating tendencies reach a certain critical level, it is perhaps reasonable to assume that they are bound to lead to the launch of a trend in the market. From then on, it is of little difference whether successive herd-followers “follow the trend” or “follow the herd”, since the two will have gradually become indistinguishable. As a result, positive feedback trading implies *trading* on the trend, while herding is a directional force capable of launching a trend. It follows that herding cannot exist in the absence of positive feedback trading, since those following a trend shaped by the herding of others must trade to its direction; it is this very element that prompted us to test for the impact of the introduction of index-futures upon herding in the market context. Thus, if the introduction of index futures has the potential of bearing an effect upon positive feedback trading at the level of the underlying spot market, it might impact upon its herding as well.

Of course, as we mentioned in Chapter 2, the inverse relationship need not hold; positive feedback trading may be the result of rational investment strategies (including, for instance, portfolio insurance and stop-loss orders) without herding being at work. Thus, a potential reduction in the positive feedback trading levels at the spot market may not necessarily reduce the corresponding herding levels of that market.

In view of the fact that the above issue appears to be both contradictory (since the causality between herding and positive feedback trading is not straightforward) and unexplored, we choose test for the hypothesis that *the introduction of index-futures leads to a significant impact upon herding in the market.*



Following our discussion above, we would like to recapitulate at this stage by drawing some attention to the fact that we test for herd behaviour in different markets on the basis of three specific market features, namely capital-gains' taxes, short-sales' restrictions and index-futures' introduction, whose association with herding has been outlined above in detail.

Our research produces the following contributions:

- extends existing empirical herding research, by testing for herding on a cross-market basis contingent upon market-features whose association with herd behaviour has not been examined before
- provides a novel framework for testing for herding across markets, as the choice of the markets is driven by the factors upon which the significance of herding is tested
- allows for extra insight into the implications of specific regulatory provisions upon the presence of herding, as the features of the markets upon which the herding-tests are conditioned constitute parts of the institutional settings of those markets

4.3 Measuring Herding: Hwang and Salmon (2004)

The efforts towards measuring herding during the 1990s culminated into two distinct lineages of measures; the former, introduced by Lakonishok et al (1992) advocated the usage of microdata (proprietary data usually involving transactions at the investor's level) to assess the existence of herding; the latter, introduced by Christie and Huang (1995) proposed a more flexible measure (at

least in terms of data) to that end. What Christie and Huang (1995) essentially argued, is that herding could be reflected in the cross-section of asset returns, in the sense that a lower cross-sectional dispersion of returns would indicate that assets moved *in tandem* with their cross-sectional mean, i.e. herded towards some sort of market consensus. Chang et al (2000) modified the herding measure of Christie and Huang (1995); whereas Christie and Huang (1995) tested for the presence of herding in the extreme tails of the return distribution, Chang et al (2000) developed a test aiming at capturing herding in the presence of nonlinearities.

Hwang and Salmon (2004) began from parallel considerations; instead of measuring herding using the cross-sectional standardized (Christie and Huang, 1995) or absolute (Chang et al, 2000) deviations of returns, they tested for herding on the basis of the cross-sectional dispersion of the factor-sensitivity of assets. More specifically, they argued that, when investors are driven by behavioural biases, their perceptions of the risk-return relationship of assets may be distorted. If they do, indeed, herd towards the market consensus, then it is possible that, as individual asset returns follow the direction of the market return, their CAPM-betas will deviate from their equilibrium values. Thus, the beta of a stock does not remain constant (as the conventional CAPM would posit), but changes with the fluctuations of investors' sentiment. As a result, the cross-sectional dispersion of the stock-betas would also be expected to be smaller, i.e. asset betas would tend towards the value of the market beta, namely unity. It is on these very premises that their herding measure is based.

More specifically, they assume the equilibrium⁷³ beta (let β_{imt}) and its behaviourally biased version (β_{imt}^b), whose relationship is assumed to be the following:

$$(E_t^b(r_{it}) / E_t(r_{mt})) = \beta_{imt}^b = \beta_{imt} - h_{mt} (\beta_{imt} - 1) \quad (1)$$

where $E_t^b(r_{it})$ is the behaviourally biased conditional expectation of excess returns of asset i at time t , $E_t(r_{mt})$ is the conditional expectation of excess returns of the market at time t and $h_{mt} \leq 1$ is a time-variant herding parameter. To measure h_{mt} (and for this reason, herding on a market-wide basis), the authors calculate the cross-sectional dispersion of β_{imt}^b , as:

$$Std_c(\beta_{imt}^b) = Std_c(\beta_{imt}) (1 - h_{mt}) \quad (2)$$

Equation (2) is rewritten as follows:

$$\log [Std_c(\beta_{imt}^b)] = \log [Std_c(\beta_{imt})] + \log (1 - h_{mt}) \quad (3)$$

in order to extract h_{mt} .

Finally, (3) is written as follows:

$$\log [Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \nu_{mt} \quad (4)$$

where

$$\log [Std_c(\beta_{imt})] = \mu_m + \nu_{mt} \quad (5)$$

with $\mu_m = E [\log [Std_c(\beta_{imt})]]$ and $\nu_{mt} \sim \text{iid} (0, \sigma_{m,\nu}^2)$

$$\text{and } H_{mt} = \log (1 - h_{mt}) \quad (6)$$

⁷³ See p.589 of their paper.

Hwang and Salmon (2004) assume that the herding parameter follows an AR(1) process and their model becomes:

$$\log [Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt} \quad (7)$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt} \quad (8)$$

where $\eta_{mt} \sim \text{iid}(0, \sigma_{m,\eta}^2)$

The above system of equations (7) and (8) accommodates herding as an unobserved component. To extract the latter, Hwang and Salmon (2004) employ the Kalman filter (see Appendix). Thus, in the above setting, the $\log [Std_c(\beta_{imt}^b)]$ is expected to vary with herding levels, the change of which is reflected through the H_{mt} . The above system of equations (7) and (8) constitutes the original expression of the Hwang and Salmon (2004) herding measure.

Special attention is drawn here to the pattern of H_{mt} . If $\sigma_{m,\eta}^2 = 0$, then $H_{mt} = 0$ and there is no herding. Conversely, a significant value of $\sigma_{m,\eta}^2$ would imply the existence of herding and (as the authors state) this would further be reinforced by a significant ϕ_m . The absolute value of the latter is taken to be smaller than or equal to one, since, as Hwang and Salmon (2004) posit, herding would not be expected to be an explosive process.

4.4 Hypotheses and our markets

4.4.1 Sample-selection: Rationale

We will now present our hypotheses on the basis of our previous discussion in Section 4.2. Before doing that however, we will focus our attention on the issue of the selection of the markets used in our work. Our intention is to show the criteria employed in the selection of those markets.

The model of Hwang and Salmon (2004) tests for herding on the basis of a set of stocks belonging to a certain index; in their paper, they assume the constituent stocks of the S&P500 (United States) and the KOSPI (South Korea) indices. However, this choice of theirs raises the issue of *comparability*. The S&P500 accounts for a fraction (about 20-25%) of the shares listed on the New York stock exchange, while the KOSPI includes every single stock listed on the Korean stock market. Although the number of stocks of both indices involved is rather similar (they assume 657 stocks from the KOSPI), we contend that the two indices are not directly comparable, as the S&P500 is a “selection” (capitalization-based) index, while the KOSPI is an all-shares’ one.

Another issue here is the one of *thin trading*. Herding studies (Hwang and Salmon, 2005; Henker et al, 2006) employ a variety of criteria to alleviate this problem; however, these studies involve the application of a single or multiple sorting criteria for a single market⁷⁴. The problem here is that markets differ in terms of structure and trading activity and as such may require different thin-

⁷⁴ Henker et al (2006) test for intraday herding in the Australian market; Hwang and Salmon (2005) test for herding in the US, UK and S. Korea, yet it is only for the US market that they apply their thin-trading-filters.

trading filters. In the end of the day, the final number of stocks using either a single or multiple filters for each market will reflect some kind of selection anyway.

The above considerations prompted us to choose to work on the premises of *top-capitalization* indices. This selection allows us both a good approximation of the total market activity as well as the inclusion of the most liquid stocks (thus, removing any thin-trading considerations). What is more, to ensure some degree of comparability, we chose to select those top-capitalization indices whose composition does not exceed 40 stocks. Finally, we chose to work only with those indices for which constituent lists were available, either from online resources or from the respective stock exchanges, in order to ensure the accuracy of the estimations of the Hwang and Salmon (2004) model.

We then proceeded to a selection of markets based upon the availability of data regarding the hypotheses involved. Grubel (2001) and Berwin (2005) provided us with evidence regarding capital gains' taxation worldwide, while Bris et al (2004) and Charoenrook and Daouk (2005) provided us with a picture of the practice of short-sales worldwide. Finally, Gulen and Mayhew (2000) provided us with information regarding the introduction of several index-futures' contracts.

In the aftermath of the above, we ended up with the following markets (indices' names in brackets): Austria (*ATX*), Belgium (*BEL20*), France (*CAC40*), Germany (*DAX30*), Hong Kong (*Hang Seng*), Netherlands (*AEX*), Portugal (*PSI20*), Switzerland (*SMI*). Apart from the indices whose names are indicative of the number of stocks they accommodate, the rest of the indices maintain a variable number of constituents, which has historically ranged within a tight band. The *ATX* has historically included 17 to 24 stocks, while similar figures apply for

the AEX, whose constituents ranged between 13 and 25 since its inception in 1983. The Swiss Market Index historically included 18 to 29 stocks in its composition, while the number of constituents of the Hang Seng index has been equal to 33 since the late 1960s.

4.4.2 Sample-selection: allocating the markets to the hypotheses

Given the above discussion, we now present the hypotheses coupled with relevant background on the markets used in each of them:

Hypothesis 1: *Herding manifests itself in significantly different fashions between markets with and without capital gains' taxes*

This hypothesis rests upon the discussion of Section 4.2.2.a and is tested here on the basis of the following markets: Austria, Belgium, Germany, France, Hong Kong, Netherlands, Portugal, Switzerland. Our sample includes both large (France, Germany, Hong Kong, Switzerland) as well as smaller (Austria, Belgium, Netherlands, Portugal) capital markets. We will now provide a summary picture of the capital gains' taxation provisions applying in each one in brief.

Austria levies taxes on capital gains realized by individuals and corporations (indigenous and overseas) in the range of 0-50 percent, subject to the holding period⁷⁵ and the nature⁷⁶ of the asset. Belgium is considered a market where capital gains are not taxed; such a perception is enforced by the fact that taxation of realized capital gains is only applicable to individuals and corporations

⁷⁵ Tax between zero and 50 percent applicable to gains realized from the sales of stocks held for less than a year; also, if the seller maintained a participation of, at least, 1 percent in the company during the previous five years. These provisions apply with certain variations to both individuals as well as corporations, be they local or overseas; see Berwin, 2005.

⁷⁶ Shares qualifying as "business assets" are not tax-exempt; otherwise, the provisions summarized in Footnote 75 apply; see Berwin, 2005.

with participations in local companies in excess of 25 percent. Germany maintains high capital gains' taxes (around half the gains realized are considered taxable at anywhere between 20 and 50 percent subject to the investor's status⁷⁷), more so for those realized within a short-term (6-12 months) holding period. Capital gains are subject to taxation at a rate of up to 27 percent in France for local individuals⁷⁸ and companies⁷⁹, while separate provisions apply for overseas investors⁸⁰. Hong Kong constitutes a jurisdiction where there exist zero capital gains' taxes, as long as the gains are not arising from "trade, profession or business" (see Grubel, 2001). Regarding the Netherlands, it is considered (Grubel, 2001) as a jurisdiction that does not tax capital gains; this is due to the fact that capital gains' taxes are very low for individuals⁸¹ (local and overseas), although corporations are subject to variable taxation⁸². Portugal taxes capital gains if the holding period is less than a year at net rates ranging between 10 and 25 percent⁸³. Finally, Switzerland does not impose taxes on capital gains, unless special circumstances materialize⁸⁴.

⁷⁷ Local individuals are subject to taxation as follows: half their capital gains are considered taxable at a rate ranging from 15 to 42 percent plus 5.5 percent plus Church tax; overseas individuals, much like in other countries, are subject to exemptions unless their shares constitute part of their undertakings in Germany. Credit institutions, financial services' institutions, financial enterprises, health and life insurance companies and pension funds are not subject to exemption; see Berwin, 2005.

⁷⁸ The figure of 27 percent includes income tax (16 percent) plus surtaxes (11 percent) and is levied upon local individuals in case the total sales of shares exceed €15,000.

⁷⁹ In the case of local corporations, capital gains are taxed at the reduced 15.72 percent rate (15 percent income tax plus surtaxes) only if the shares sold were held for more than two years, otherwise, normal corporate profit tax rates apply (33.33 percent plus surtaxes); see Berwin, 2005.

⁸⁰ Non-resident individuals and corporations are subject to capital gains' tax (16 percent) only if they maintained a participation in excess of 25 percent during the previous five years; see Berwin, 2005.

⁸¹ Shareholder-ownerships in excess of 5 percent are subject to capital gains' tax of 25 percent. Otherwise, local individuals are taxed only upon 4 percent of the average fair market value of the shares measured at the start and end of the year at a rate of 30 percent, while overseas individuals are not subject to tax; see Berwin, 2005.

⁸² See Berwin (2005) for details.

⁸³ Local individuals are subject to a tax rate of 10 percent; the latter applies to overseas individuals subject to certain clauses. Local and overseas corporations are subject to capital gains' taxes equal to 25 percent, although several exemptions due to legal reasons may apply.

⁸⁴ See Berwin (2005).

Thus, the above presentation seems to indicate that Belgium, Hong Kong, the Netherlands and Switzerland appear to be the jurisdictions in our sample with the most liberal treatment of capital gains' taxation compared to the other four markets.

Hypothesis 2: *The introduction of short-sales bears a negative impact upon herding*

As short-sales' constraints have been found to be associated with the overvaluation of assets (Miller, 1977), we test whether they are also associated with higher herding, as the latter has the potential of generating overpricing. We test for this hypothesis using the markets of Hong Kong and Portugal. The choice of these two markets was based upon the fact that the rest of the markets of our sample have legally allowed short-selling for decades and, as such, it is not possible to test for the impact of the latter's introduction.

Regarding Hong Kong, the local Stock Exchange Authorities first allowed short sales in January 1994 for an initial sample of seventeen specifically designated stocks. Since March 1996 the eligibility for short-selling was extended to all the constituents of the underlying indices⁸⁵ of index-based derivatives who met certain capitalization⁸⁶ and turnover⁸⁷ requirements (Ho et al, 2002; Chang and Yu, 2004). In the case of Portugal our information stems from Lobao and Serra (2006), who note that short-selling constraints were gradually removed during 1999.

⁸⁵ Such indices are: the Hang Seng, the Mini Hang Seng Index, the H-Shares Index and the FTSE/Xinhua China 25 Index.

⁸⁶ Minimum capitalization must equal HK\$1 billion.

⁸⁷ Minimum turnover-to-capitalization ratio must be no less than 0.4.

Hypothesis 3: *The introduction of index-futures bears a significant impact upon herding in the market*

We test for this hypothesis using the following markets: Germany, Hong Kong and the Netherlands. We would like to devote some space to explain why, even though all the markets in our sample have maintained index-futures since identifiable points in the past, we decided to restrict our tests to these three markets.

In certain cases (Belgium, France, Portugal, Switzerland) the introduction of index-futures took place shortly after (less than four years) the launch of the underlying index⁸⁸. As a result, the pre-futures' introduction period grows very small, thus leading to estimation problems, since our herding-measure involves monthly observations. We also chose not to test for Austria due to the limited availability of historical constituent lists for the ATX-index for the pre-futures' period⁸⁹. Index-futures were introduced on the Hang Seng (Hong Kong) in May 1986, the AEX (Netherlands) in October 1988 and the DAX30 (Germany) in November 1990.



In all cases, and based on the premises of the Hwang and Salmon (2004) model, the significance (or not) of herding would be established through the results for the coefficients of the state equation:

⁸⁸ *The relevant index-futures' introduction dates (underlying spot-market index launch dates in brackets) are: BEL20: October 1993 (March 1991); CAC40: November 1988 (January 1988); PSI20: June 1996 (January 1993); SMI: November 1990 (July 1988).*

⁸⁹ *The ATX-index futures' contract was launched as of August 1992, yet constituent lists for that index are available since November 1991.*

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}$$

As mentioned above (Section 4.3), **herding is significant if: a) the ϕ_m were to be significant and b) the variance ($\sigma_{m,\eta}^2$) of η_{mt} is found to be significant.**

4.5 Data and Methodology

4.5.1 Data

We use daily data for our sample-markets mentioned previously (Austria, Belgium, France, Germany, Hong Kong, Netherlands, Portugal, Switzerland); the data relate to the closing prices of the following indices: *ATX* (Austria), *BEL20* (Belgium), *CAC40* (France), *DAX30* (Germany), *Hang Seng* (Hong Kong), *AEX* (Netherlands), *PSI20* (Portugal), *SMI* (Switzerland). All data on the above indices' closing prices as well as the closing prices of their historical constituent stocks were collected from Datastream. Data on the historical constituent lists of these indices were obtained from the respective stock exchanges and exchange-related websites.

To calculate the excess returns for the Hwang and Salmon (2004) model, we used the following risk-free rates for each market, which we obtained from Datastream:

- Austria (3-month VIBOR)
- Belgium (3-month treasury-bill)
- France (3-month PIBOR)
- Germany (3-month interbank rate)

- Hong Kong (Prime Rate before 30/12/1985; 3-month deposit rate afterwards)
- Netherlands (3-month interbank rate)
- Portugal (3-month deposit-rate up to 31/12/1998; 3-month Euribor after 1/1/1999)
- Switzerland (3-month interbank rate)

4.5.2 Methodology

We test for herding using the original Hwang and Salmon (2004) model in line with the discussion carried out in Section 4.3.

We first estimate the OLS-estimates of the betas using daily excess returns within monthly windows in the standard market model:

$$r_{itd} = \alpha_{it}^b + \beta_{imt}^b r_{mtd} + \varepsilon_{itd} \quad (9)$$

where the subscript td indicates daily data for month t .

Having estimated these monthly betas for the stocks corresponding to each market index in month t , we then estimate their cross-sectional standard deviation for that month, thus constructing a monthly time-series of it. As Hwang and Salmon (2004) argue, the choice of monthly windows is driven by both estimation considerations (to reduce the estimation error of the betas) as well as practical ones (to maintain a number of observations sufficient enough to track down herding).

We test for the first hypothesis using the 1/1/1996-31/12/2005 window for all eight markets of that hypothesis' sample. For the second and third hypotheses, we test for herding in the period preceding, as well as the period following the

introduction of short-sales and index-futures respectively. Our estimations for the second and third hypotheses are conducted on the basis of time-windows of 4 and 5 years before and after the introduction-point in order to ensure the robustness of our findings.

More specifically, in hypothesis 2, we test for herding in Hong Kong for the *1/3/1992-31/3/1996* and *1/4/1996-31/3/2000* periods (± 4 years) as well as the *1/3/1991-31/3/1996* and *1/4/1996-31/3/2001* periods (± 5 years); in the case of Portugal, we test for herding for the *1/1/1996-31/12/1999* and *1/1/2000-31/12/2003* periods (± 4 years) as well as the *1/1/1995-31/12/1999* and *1/1/2000-31/12/2004* periods (± 5 years).

Finally, in hypothesis 3, we test for herding in Germany for the *1/12/1986-1/12/1990* and *1/12/1990-30/11/1994* periods (± 4 years) as well the *1/12/1985-1/12/1990* and *1/12/1990-30/11/1995* periods (± 5 years); in Hong Kong for the *1/5/1982-30/4/1986* and *1/5/1986-30/4/1990* periods (± 4 years) as well the *1/5/1981-30/4/1986* and *1/5/1986-30/4/1991* periods (± 5 years); in the case of the Netherlands, we test for herding for the *1/11/1984-31/10/1988* and *1/11/1988-31/10/1992* periods (± 4 years) as well as the *1/11/1983-31/10/1988* and *1/11/1988-31/10/1993* periods (± 5 years).

4.5.3 Descriptive Statistics

Table 4.1 presents some statistics related to the estimated logarithmic cross-sectional standard deviation of the betas of the eight market indices' portfolios for each of the three hypotheses. As indicated by the table, the logarithmic cross-sectional standard deviation of the betas does not indicate any departures from normality for any single market. Therefore, the state-space model

of Hwang and Salmon (2004) described previously can be legitimately estimated using the Kalman filter for our hypotheses.

4.6 Results

4.6.1 Herding and capital-gains' taxation

Table 4.2 reports the results from the Hwang and Salmon (2004) model regarding the first hypothesis, namely that herding is expected to manifest itself in significantly different fashions between markets with and without capital gains' taxes. Our interest here is concentrated on the estimates for the parameters of the state-equation, namely ϕ_m and $\sigma_{m,\eta}$, since significant values for those two would indicate the presence of significant herding.

As Table 4.2 illustrates, herding is persistent for all eight market indices, as the persistence parameter (ϕ_m) is significant for all of them (1% level). This finding is further corroborated by the estimates for the standard deviation ($\sigma_{m,\eta}$) of the state-equation error (η_{mt}) which are significant at the 10% level for all markets. The value of μ_m reflects the mean level of the logarithmic cross-sectional standard deviation of the index-portfolio betas as adjusted through herding (expressed here through H_{mt}) and is found to be statistically significant at the 1% level within a given band (ranging from approximately -0.14 to -0.51). The logarithmic cross-sectional standard deviation of the index-portfolio betas is found to maintain a statistically significant presence in all markets as the estimates of the $\sigma_{m,v}$ indicate.

In six markets (Austria, France, Germany, Hong Kong, Portugal and Switzerland) the persistence parameters are greater than 0.9, while in the Netherlands the value of ϕ_m is about 0.88. Belgium records the smallest value of

Table 4.1: Descriptive Statistics
 (referring to the logarithmic cross-sectional standard deviations for each market index and each hypothesis)

Markets	Sample Mean	Standard Error	Skewness	Kurtosis	Jarque-Bera
↓	<i>Hypothesis 1: 1/1/1996-31/12/2005</i>				
Austria	-0.2234158832	0.1342140749	0.22258	0.19478	1.18050
Belgium	-0.2825896370	0.1122192060	0.13709	-0.12257	0.45101
France	-0.3125183103	0.1207213549	0.36705	-0.41407	3.55173
Germany	-0.3945343763	0.1299474969	0.01621	0.19207	0.18972
Hong Kong	-0.3307889647	0.0916978829	-0.36346	-0.10045	2.69256
Netherlands	-0.2576401724	0.1576873969	0.17677	-0.52003	1.97714
Portugal	-0.3528043817	0.3331163297	0.19365	0.57760	3.14357
Switzerland	-0.3286169342	0.1424455221	0.28490	0.31734	2.12685
	<i>Hypothesis 2</i>				
Hong Kong ±4 years (1/3/1992-31/3/2000)	-0.4112328731	0.0944649980	-0.15180	-0.37219	0.94200
Hong Kong ±5 years (1/3/1991-31/3/2001)	-0.3976947274	0.1008175115	-0.09728	-0.39801	0.98951
Portugal ±4 years (1/3/1996-31/12/2003)	-0.2248021752	0.1315369386	-0.33490	-0.12556	1.85755
Portugal ±5 years (1/3/1995-31/3/2004)	-0.1973552378	0.1422074209	-0.10973	0.02044	0.24289
	<i>Hypothesis 3</i>				
Germany ±4 years (1/12/1986-30/11/1994)	-0.5034817020	0.0987843365	0.33602	0.54338	2.98758
Germany ±5 years (1/12/1985-30/11/1995)	-0.4975685361	0.0950987156	0.26159	0.47771	2.50962
Hong Kong ±4 years (1/5/1982-30/4/1990)	-0.3408653169	0.0971141691	-0.31868	-0.62475	3.18614
Hong Kong ±5 years (1/5/1981-30/4/1991)	-0.3412776948	0.0976598513	-0.35591	-0.47698	3.67105
Netherlands ±4 years (1/11/1984-31/10/1992)	-0.3563511114	0.1414503362	0.20025	0.15442	0.72929
Netherlands ±5 years (1/11/1983-31/10/1993)	-0.3362892799	0.1463154912	0.30713	0.22986	2.16869

ϕ_m equal to approximately 0.78. In terms of the absolute size of the persistence parameters, the markets can be ranked as follows (in descending order): Germany,

France, Portugal, Austria, Hong Kong, Switzerland, Netherlands, Belgium. Thus, these initial observations seem to suggest the presence of more persistent herding for markets where capital gains are subject to taxation.

We then tried to assess the significance of the difference in the persistence of herding across markets; to that end, we tested for the significance of the difference in ϕ_m between markets with and markets without capital gains' taxes. Results from the Wald-tests in Table 4.3 indicate that the persistence parameter ϕ_m is significantly higher in markets where capital gains' taxes exist compared to those with minimal or zero capital gains' taxes. This is the case with Germany, Portugal, and to an extent, France (which appears to maintain insignificantly higher herding levels only compared to Hong Kong); Austria, finally, is the exception to the rule, as its herding is significantly higher compared only to Belgium.

To gain further comparative insight into how smooth the presence of herding is, we report the figures for the signal-to-noise ratio, which, in line with Hwang and Salmon (2004), is denoted here as $\sigma_{m,\eta} / \text{S.D. (log-CXB)}$; as the notation suggests, the signal-to-noise ratio for each market is calculated by dividing the $\sigma_{m,\eta}$ by the time series standard deviation of the logarithmic cross-sectional standard deviation of the betas and provides an indication of the proportion of the variability of the logarithmic cross-sectional standard deviation of the betas explained by herding. As Hwang and Salmon (2004) showed empirically in their paper, the bigger the value of the signal-to-noise ratio, the less smooth over time herding becomes. The signal-to-noise ratios assume values around 0.2 for five markets (Austria, France, Germany, Hong Kong, Portugal),

Table 4.2: Results from the herding tests (Hwang and Salmon, 2004): Hypothesis 1

$$\log [Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + v_{mt}, \quad v_{mt} \sim iid(0, \sigma_{m,v}^2)$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}, \quad \eta_{mt} \sim iid(0, \sigma_{m,\eta}^2)$$

	Austria	Belgium	France	Germany	Hong Kong	Netherlands	Portugal	Switzerland
ϕ_m	0.931638304 (0.037035887)***	0.781012913 (0.095883896)***	0.963833797 (0.027187920)***	0.990372783 (0.014418227)***	0.930112665 (0.040169540)***	0.877778667 (0.046945119)***	0.970004762 (0.023353644)***	0.902389489 (0.044112704)***
μ_m	-0.244844170 (0.036371279)***	-0.285879904 (0.016162451)***	-0.313978394 (0.038358971)***	-0.510093815 (0.046744981)***	-0.331300893 (0.023088009)***	-0.273552343 (0.043598515)***	-0.141689971 (0.042873861)***	-0.334083933 (0.036339868)***
$\sigma_{m,\eta}$	0.033338986 (0.000517685)**	0.033395613 (0.000602196)*	0.026042734 (0.000284524)**	0.022811028 (0.000263191)**	0.02089531 (0.000223756)*	0.067285883 (0.001200916)***	0.025874215 (0.000301508)**	0.044057587 (0.000783080)**
$\sigma_{m,v}$	0.100716791 (0.001516019)***	0.098301348 (0.001447166)***	0.07709271 (0.000881763)***	0.091796095 (0.001203310)***	0.07296285 (0.000778797)***	0.072589758 (0.001136900)***	0.093993548 (0.001269822)***	0.099146941 (0.001564504)***
$\sigma_{m,\eta} /$ S.D. (log- CXB)	0.248401565	0.297592673	0.215725993	0.175540342	0.227871242	0.426704251	0.208868714	0.309294295

NB: *: indicates significance at the 1% level; **: indicates significance at the 5% level; ***: indicates significance at the 10% level. Parentheses include the standard errors of the estimates.

Table 4.3: Results from the Wald-tests: Hypothesis 1

	Belgium	Hong Kong	Netherlands	Switzerland
Austria	0.1506254 (16.540585)***	0.0015257 (0.001697)	0.0538597 (2.114859)	0.0292489 (0.623693)
France	0.1828208 (45.216780)***	0.0337211 (1.538340)	0.0860551 (10.018474)***	0.0614443 (5.107535)**
Germany	0.2093598 (210.844942)***	0.0602601 (17.467722)***	0.1125941 (60.982848)***	0.0879833 (37.237177)***
Portugal	0.1889918 (65.490280)***	0.0398921 (2.917860)*	0.0922261 (15.595465)***	0.0676153 (8.382630)***

NB: *: indicates significance at the 1% level; **: indicates significance at the 5% level; ***: indicates significance at the 10% level. Parentheses include the standard errors of the estimates.

while they are approximately equal to 0.3 in the cases of Belgium and Switzerland; it is worth noting that the Netherlands furnish us with the highest signal-to-noise ratio (about 0.43). In terms of the absolute size of the signal-to-noise ratios, the markets can be ranked as follows (in descending order): Netherlands, Switzerland, Belgium, Austria, Hong Kong, France, Portugal, Germany. Thus, the results from the signal-to-noise ratios indicate that herding appears smoother in markets where capital gains are taxed.

In view of the above, our findings indicate that herding appears more persistent and smooth in markets that impose taxes upon capital gains. Consequently, it follows that these results support our first hypothesis, namely that herding tends to manifest itself in significantly different fashions between markets with and markets without capital gains' taxes.

4.6.2 Herding and short-selling constraints

Table 4.4 reports the results from the Hwang and Salmon (2004) model regarding the second hypothesis, according to which herding is expected to be more significant prior to the introduction of short-selling; as we have already mentioned, we are testing for this hypothesis for the Hong Kong and Portuguese markets.

For the Hong Kong market we use March 1996 as the cut-off point defining the pre- versus post-short-sales' introduction periods, in line with what we mentioned in Section 4.4.2. According to Table 4.4, herding appears highly persistent during both sub-periods with the persistence parameter (ϕ_m) being significant using both four- as well as five-year windows (1% level) before and

after the introduction-date. However, as the estimates for the standard deviation ($\sigma_{m,\eta}$) of the state-equation error (η_{mt}) are found to be insignificant for both sub-periods, this seems to suggest that herding towards the Hang Seng index both prior to as well as following the wider introduction of short-sales in the Hong Kong market is probably insignificant.

The relevant Wald-tests show us that the difference in the persistence parameters of the two periods is insignificant, which implies that the wider introduction of short-sales in the Hong Kong market probably had a negligible effect over the herding levels towards the Hang Seng portfolio. Interestingly enough, the persistence parameter prior to and after the introduction of short-sales appears to exhibit certain differences when looking at different window-lengths. Although the usage of five-year windows indicates that herding has maintained its persistence levels around the same values, the results we obtain from the four-year windows indicate that the drop in the persistence parameters following the removal of short-selling constraints is rather sharp (from 0.72 down to 0.41). Although the values of the persistence parameters prior to the removal of short-sales' constraints appear to be around the same levels (0.7–0.8), this is not the case following the removal of short-sales' constraints; while the four-year windows provide us with an estimate for the ϕ_m equal to 0.41, the corresponding one for the five-year windows rises to 0.87. The five-year windows here include a year more than the four-year ones, namely 2001 (see Table 4.4) and it is perhaps this that might constitute the reason underlying the significant discrepancy in the two estimates of the persistence parameter⁹⁰.

⁹⁰ Possible reasons for the impact of year 2001 may include: the outbreak of the DotCom bubble; the massive divestiture of Hang-Seng-stocks bought by the Hong Kong Government during mid-

For the Portuguese market we use December 1999 as the cut-off point defining the pre- versus post-short-sales' introduction periods, since most constraints on short-sales were lifted during that year (Lobao and Serra, 2006). The results reported in Table 4.4 suggest that herding appears highly persistent during both sub-periods, with the persistence parameter (ϕ_m) being highly significant (1% level) using both four- as well as five-year windows before and after the introduction-date. Having said that, however, the estimates for the standard deviation ($\sigma_{m,\eta}$) of the state-equation error (η_{mt}) are found to be insignificant for both sub-periods, thus implying the absence of herding towards the PSI20 index both prior to as well as following the removal of short-sales' constraints in the Portuguese market. Much like with the case of the Hong Kong market above, the estimates of the persistence parameters for both sub-periods were found to be insignificantly different from each other. Contrary, however, to Hong Kong, the five-year windows did not produce substantially different results from the four-year windows regarding the persistence parameter before and after the wider introduction of short sales.

1998, in order to mitigate against speculative short-selling pressure on stock prices during the Asian Crisis.

Table 4.4: Results from the herding tests (Hwang and Salmon, 2004): Hypothesis 2

$$\log [Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + v_{mt}, \quad v_{mt} \sim iid(0, \sigma_{m,v}^2)$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}, \quad \eta_{mt} \sim iid(0, \sigma_{m,\eta}^2)$$

	Hong Kong				Portugal			
	±4 years		±5 years		±4 years		±5 years	
	(1) 1/3/1992- 31/3/1996	(2) 1/4/1996- 31/3/2000	(1) 1/3/1991- 31/3/1996	(2) 1/4/1996- 31/3/2001	(1) 1/3/1996- 31/12/1999	(2) 1/1/2000- 31/12/2003	(1) 1/3/1995- 31/12/1999	(2) 1/1/2000- 31/12/2004
ϕ_m	0.725665728 (0.223240277)***	0.419656659 (0.265803216)***	0.861366952 (0.139693770)***	0.877347394 (0.095971707)***	0.988553534 (0.025833735)***	0.747827175 (0.214039680)***	0.995937248 (0.019022129)***	0.767883409 (0.223875385)***
μ_m	-0.431689950 (0.019334544)***	-0.383163080 (0.015382596)***	-0.421819166 (0.017847981)***	-0.367041526 (0.025279050)***	-0.115518754 (0.058817119)**	-0.175819008 (0.021067597)***	-0.047068330 (0.061429046)	-0.173337210 (0.016399961)***
$\sigma_{m,\eta}$	0.030605751 (0.000841997)	0.049488302 (0.001285195)	0.015682442 (0.000323308)	0.026547222 (0.000484077)	0.031754685 (0.000678021)	0.028673263 (0.000899115)	0.030990611 (0.000572243)	0.019692943 (0.000558035)
$\sigma_{m,v}$	0.083136232 (0.001663623)***	0.067411809 (0.001403540)***	0.095446938 (0.001751243)***	0.075134393 (0.001212553)***	0.097632587 (0.002221154)***	0.099672268 (0.002277046)***	0.10724941 (0.002339871)***	0.098308489 (0.001890670)***
$\sigma_{m,\eta}/S.D.$ (log-CXB)	0.324030291	0.565417383	0.155739943	0.289874221	0.235318636	0.261973299	0.182483249	0.189774564
Wald-test [(2)-(1)]	-0.3060091 (1.325404)		0.0159804 (0.027726)		-0.2407264 (1.264907)		-0.2280538 (1.037677)	

NB: *, indicates significance at the 1% level; **, indicates significance at the 5% level; ***, indicates significance at the 10% level. Parentheses include the standard errors of the estimates.

As a result, the above findings seem to indicate that the wider introduction of short-sales and the removal of their constraints appears to bear little effect over the presence of herding towards the index-portfolio; our investigation of the Hong Kong and Portuguese markets suggests that herding towards the Hang Seng and PSI20 portfolios respectively appears insignificant in both sub-periods as well as insignificantly different between them. Consequently, the evidence presented above is not able to confirm our second hypothesis, i.e. the introduction of short-sales does not lead to reduced herding levels.

4.6.3 Herding and the introduction of index-futures

Table 4.5 reports the results for the markets (Germany, Hong Kong, Netherlands) falling under the auspices of our third hypothesis, according to which the introduction of index-futures bears a significant impact upon herding in the market.

In the case of the German market, herding towards the DAX30-portfolio appears highly persistent during both sub-periods using both four- and five-year windows before and after the index-futures' introduction-date (November 1990), as the persistence parameter (ϕ_m) is highly significant (1% level).

Contrary to that, the estimates of the standard deviation ($\sigma_{m,\eta}$) of the state-equation error (η_{mt}) appear insignificant for both sub-periods, thus implying the absence of herding. What is more, the persistence parameters of the two sub-periods are found to be insignificantly different from each other, which leads us to the conclusion that the introduction of index-futures on the DAX30 had no impact upon the herding levels towards the portfolio of that index. In relation to that, note

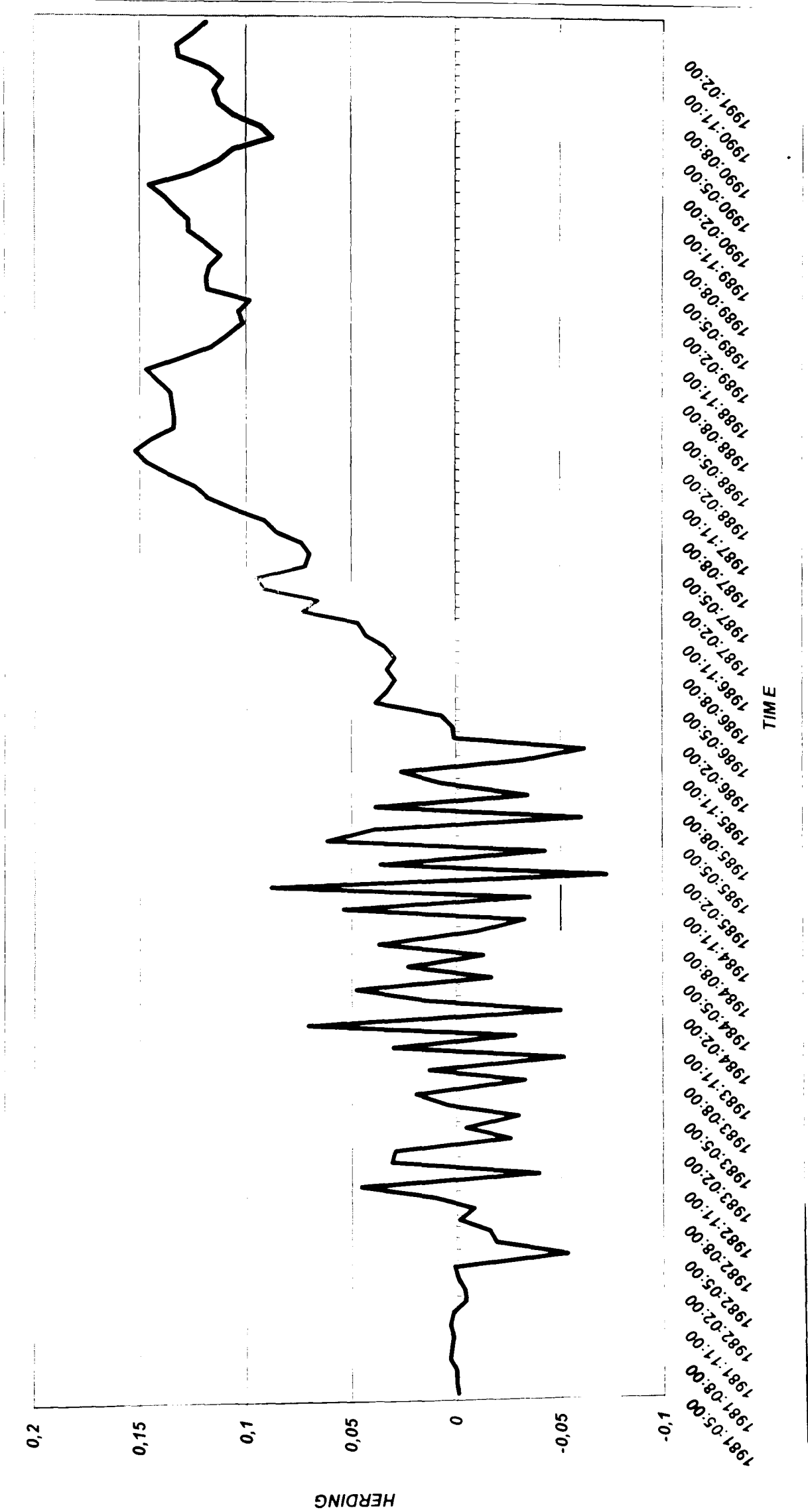
also that the values of the persistence parameter both prior to as well as after the introduction of index-futures on the DAX30 appear to be very similar in size, thus providing further robustness on our results.

Regarding the Hong Kong market, herding towards the Hang Seng portfolio remains highly persistent during both sub-periods using both four- and five-year windows before and after the index-futures' introduction-date (May 1986), as the persistence parameter (ϕ_m) is found to be statistically significant (10% level) in all cases. An interesting feature of our results is the switch of the sign of ϕ_m from negative (prior to the introduction of index-futures) to positive (following the introduction of index-futures), which indicates that herding (as defined by the AR(1) process of the state-equation) exhibits negative autocorrelation prior to May 1986 and positive autocorrelation following that date. Furthermore, the estimates of the standard deviation ($\sigma_{m,\eta}$) of the state-equation error (η_{mt}) appear highly significant (5% level) for both sub-periods, thus implying the presence of herding. What is more, the persistence parameters of the two sub-periods are found to be significantly different (1% level) from each other, thus leading us to the conclusion that the introduction of index-futures on the Hang Seng had a significant impact upon the herding levels towards the portfolio of that index. In relation to that, note also that the values of the persistence parameter both prior to as well as after the introduction of index-futures on the Hang Seng appear to be very similar in size irrespective of window-length, thus providing further robustness on our results. Finally, we should note that the values of the signal-to-noise ratios are notably large (over 0.6), thus indicating that herding during both sub-periods does not evolve smoothly.

To allow a visual representation of this rather interesting behaviour of herding prior to and after the introduction of index-futures on the Hang Seng we provide Figure 4.1, which depicts the evolution of herding between May 1981 and April 1991. As the Figure illustrates, herding presents us with interchanging swings (upwards and downwards) prior to 1986 which are in line with the negative autocorrelation in its pattern we documented for the period prior to May 1986 (i.e. pre-futures' introduction period). However, after February 1986 herding begins to assume a rather clear ascending direction in its movement, which is also in line with the positive autocorrelation in its pattern we documented for the period following May 1986 (i.e. post-futures' introduction period).

We conclude with the Dutch market, where herding towards the AEX-portfolio appears highly persistent during both sub-periods using both four- and five-year windows before and after the index-futures' introduction-date (October 1988), as the persistence parameter (ϕ_m) is statistically significant (5% level). Contrary to that, the estimates of the standard deviation ($\sigma_{m,\eta}$) of the state-equation error (η_{mt}) appear insignificant for both sub-periods, thus implying the absence of herding. What is more, the persistence parameters for the two sub-periods are found to be insignificantly different from each other, thus leading us to the conclusion that the introduction of index-futures on the AEX had no impact upon its herding levels. In relation to that, the values of the persistence parameter both prior to as well as after the introduction of index-futures on the AEX appear to be very similar in size, thus providing further robustness on our results.

Figure 4.1: Herding towards the Hang Seng index (May 1981 – April 1991)



Our results thus indicate that the introduction of index-futures had an insignificant impact upon the herding towards the DAX30- and AEX-portfolios; what is more, herding was found to be insignificant both before as well as after the introduction of index-futures in those two markets. The case of Hong Kong provides us with a rather interesting picture, as the introduction of index-futures on the Hang Seng had a significant impact on the herding towards that index, as it led to the switch of the herd's persistence sign. Consequently, our results seem to provide us with mixed evidence regarding our third hypothesis; in other words, the introduction of index-futures does not bear a significant impact over herding in all markets.

4.6.4 Discussion

Following the presentation of our results we shall now attempt to associate them with the existing literature findings on herding. We shall first begin from the second and third hypotheses (i.e. the hypotheses related to the impact of the introduction of short-selling and index-futures over herding respectively) by arguing that in the absence of any relevant literature on the subjects they touch upon, it is hard to draw any parallel with existing herding research.

However, our results from the first hypothesis provide us with a rather more interesting picture. We mentioned in the beginning (4.2.2.a) that, according to Kim and Wei (2002a), offshore funds as well as funds from Hong Kong and Singapore herded less in South Korea during the Asian crisis (1997-1999) compared to their US and European counterparts. Such behaviour was ascribed

Table 4.5: Results from the herding tests (Hwang and Salmon, 2004): Hypothesis 3

$$\log [Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + v_{mt}, v_{mt} \sim iid(0, \sigma_{m,v}^2)$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}, \eta_{mt} \sim iid(0, \sigma_{m,\eta}^2)$$

	Germany				Hong Kong				Netherlands			
	±4 years		±5 years		±4 years		±5 years		±4 years		±5 years	
	(1) 1/12/1986- 1/12/1990	(2) 1/12/1990- 30/11/1994	(1) 1/12/1985- 1/12/1990	(2) 1/12/1990- 30/11/1995	(1) 1/5/1982- 30/4/1986	(2) 1/5/1986- 30/4/1990	(1) 1/5/1981- 30/4/1986	(2) 1/5/1986- 30/4/1991	(1) 1/11/1984- 31/10/1988	(2) 1/11/1988- 31/10/1992	(1) 1/11/1983- 31/10/1988	(2) 1/11/1988- 31/10/1993
ϕ_m	0.908044344 (0.090694279)***	0.908543831 (0.075934441)***	0.873316271 (0.101458602)***	0.872098252 (0.083218843)***	-0.512842236 (0.186321523)***	0.375817340 (0.214599262)***	-0.467415336 (0.176299714)***	0.279393960 (0.156803259)*	0.847223051 (0.112499995)***	0.919161414 (0.265138541)***	0.845866913 (0.100965026)***	0.863559647 (0.082280807))***
μ_m	-0.506153499 (0.022225241)***	-0.513426931 (0.033681313)***	-0.494485736 (0.017996747)***	-0.497966259 (0.026066792)***	-0.291284639 (0.008059467)***	-0.390240571 (0.017610190)***	-0.290366272 (0.006864391)***	-0.391034464 (0.015809618)***	-0.389790974 (0.035812471)***	-0.315926915 (0.019720331)***	-0.383032857 (0.029915656)***	-0.297599480 (0.036382566)***
$\sigma_{m,\eta}$	0.015185355 (0.000234023)	0.027422217 (0.000528500)	0.016262995 (0.000256427)	0.027658543 (0.000503519)	0.043301166 (0.000786504)**	0.066877171 (0.001639467)***	0.043013358 (0.000662151)***	0.08253143 (0.001630011)***	0.037540778 (0.001158827)	0.006340189 (0.000210615)	0.034700375 (0.000884310)	0.041391436 (0.001092935)
$\sigma_{m,v}$	0.084806102 (0.001567018)***	0.084241836 (0.001659627)***	0.082497861 (0.001338284)***	0.083863502 (0.001477766)***	0.047804372 (0.000809769)***	0.06099327 (0.001595265)**	0.044247712 (0.000662176)***	0.045472849 (0.001510323)***	0.12779822 (0.003761265)***	0.121510473 (0.003052948)***	0.116339963 (0.002797163)***	0.113430093 (0.002742029)***
$\sigma_{m,\eta}/$ S.D. (log- CXB)	0.163984354	0.259738323	0.181832657	0.273306056	0.617086718	0.701512104	0.648889281	0.841949666	0.255587167	0.051242208	0.259316057	0.295810934
Wald- test [(2)-(1)]	0.0004995 (4.326839e-05)		-0.001218 (0.000214)		0.8886595 (17.148037)***		0.7468089 (22.683458)***		0.0719384 (0.073617)		0.0176935 (0.046237)	

NB: *: indicates significance at the 1% level; **: indicates significance at the 5% level; ***: indicates significance at the 10% level. Parentheses include the standard errors of the estimates.

by the authors to the fact that these jurisdictions (“offshore”, Hong Kong and Singapore) do not tax capital gains realized by funds registered with them, as opposed to the US and European jurisdictions. In our case, we found that market-wide herding appears to be smoother and more persistent in markets with zero or very low capital gains’ taxes. Although no direct comparison is possible here (our research involves market-wide herding at the top-capitalization index-level in many markets, while Kim and Wei (2002a) study herding on behalf of overseas institutional investors only for the universe of stocks listed in South Korea), results seem to point towards the direction of a relatively favorable impact of the presence of capital gains’ taxation over herding. It is our understanding that this constitutes an issue meriting extensive future research.

4.7 Conclusion

Herding as a phenomenon in the stock market context has been the subject of substantial research, both at the analytical as well as the empirical level (Bikhchandani and Sharma, 2001; Hirshleifer and Teoh, 2003). Analytical research has thus far provided us with the theoretical underpinnings of herd behaviour regarding its sources and motivations, while empirical research has produced an ever-increasing amount of results regarding herding across various markets. However, little attention has been dedicated to the comparative empirical examination of herding, i.e. its study across a variety of market settings; even the few cross-market studies (Chang et al, 2000; Hwang and Salmon, 2004) on herding do not approach the issue from a distinctive comparative angle.

We aim at contributing to this point by investigating herding across several markets on the premises of specific regulatory features that, as the Finance literature has indicated, are capable of exerting influence over the presence of herding. More specifically, we test for the impact of capital gains' taxes, short-sales' constraints and the introduction of index-futures over the significance of herd behaviour. Our tests involved a sample of eight (top-capitalization) market indices and covered a variety of time-periods from the early 1980s until 2005.

Our results indicate that herding tends to manifest itself in significantly different fashions between markets that tax and markets that do not tax capital gains; more specifically, we found herding to exhibit more persistence and smoothness in those jurisdictions that impose taxes on capital gains. We also documented the absence of any impact upon herding in the aftermath of the removal of most major short-sales' constraints. Finally, our results regarding the impact of the introduction of index-futures upon herding show us that such an impact may exist in certain markets, yet not in others.

Our results indicate that certain regulatory factors (capital gains' taxation) bear an overall significant impact over the manifestation of herding, while others (the removal of short-sales' constraints) do not or (in the case of index-futures' introduction) may not bear a similar impact across all markets. It is our understanding that our research constitutes a useful first stimulus for further research in this area, as the study of herding on these premises can well be expanded using a wider array of markets and/or herd-related regulatory features.

Appendix

The Kalman Filter is a recursive algorithm aiming at estimating and evaluating dynamic linear models in what is known as the form of a “state-space representation”. Its output generates mean square error forecasts and its construction involves two equations. The first one is known as the “measurement” (or “observation” or “system” or “transition”) equation and relates an observable variable to the states of an unobservable one. Put it this way, the measurement equation defines the dynamic evolution of an observed variable described in terms of an unobserved one; the latter’s functional form is, in turn, defined through what is known as the “state equation”.

To illustrate the above, let us assume (Hamilton, 1994) the following dynamic linear system:

$$\xi_t = F \xi_{t-1} + v_t \quad (1)$$

$$y_t = A' \chi_t + H' \xi_t + w_t \quad (2)$$

where:

y_t = $n \times 1$ vector of the observed variable at time t

ξ_t = $r \times 1$ vector of the unobserved variable (“state vector”)

A', F', H' = matrices of parameters of dimension $(n \times k)$, $(r \times r)$ and $(n \times r)$

respectively.

$\nu_t = r \times 1$ white noise vector [$\nu_t \sim \text{iid}(0, \sigma_\nu^2)$]

$w_t = n \times 1$ white noise vector [$w_t \sim \text{iid}(0, \sigma_w^2)$]

In the above setting, equation (1) would be the measurement equation and equation (2) the state equation. In its commonest form, the error term vectors ν_t and w_t are assumed to be uncorrelated, mean zero and normally distributed while their respective variances (σ_ν^2, σ_w^2) are assumed to be known. The Kalman filter provides recursive estimates for ξ_t on the premises of past and present information of the observable variables as well as existing estimates of ξ_t itself (see Hamilton, 1994 for a detailed description of the algorithm's process).

In the context of the Hwang and Salmon (2004) herding model we have the logarithmic cross-sectional standard deviation of the stocks' monthly betas which is the observable variable with the following functional form (see Chapter 4 for more on its derivation):

$$\log [\text{Std}_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \nu_{mt}, \text{ where } \nu_{mt} \sim \text{iid}(0, \sigma_{m,\nu}^2).$$

The above represents the measurement equation of the model's dynamic linear system where the observable variable ($\log [\text{Std}_c(\beta_{imt}^b)]$) is conditioned upon an unobservable one (H_{mt}) reflective of changes in market-wide herding. Under the authors' assumption that herding follows an AR(1) process, the state equation for this system is:

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}, \text{ where } \eta_{mt} \sim \text{iid}(0, \sigma_{m,\eta}^2).$$

Using the Kalman filter, the H_{mt} is extracted which, in turn enables us to calculate market-wide herding through equation (6) in Chapter 4 and depict it diagrammatically.

Chapter 5

Institutional Herding Under Various Market Conditions: Evidence from Portugal

5.1 Introduction

The issue of whether institutional investors are susceptible to exhibiting herd behaviour in their trading conduct has been at the forefront of research in behavioural Finance during the last decade (Bikhchandani and Sharma, 2001), more so due to the wider availability of databases related to the transactions and portfolio-holdings of fund managers. The possibility of herd-instincts arising within the ranks of the latter and the implications of this with regards to stock returns as a result of the funds' leverage in the marketplace (Wermers, 1999) have constituted the motivation underlying much of recent research in herd behaviour (Hirshleifer and Teoh, 2003).

Empirical research on institutional herding has gradually been evolving since the early 1990s and has been mostly based upon the methodological approach proposed by Lakonishok et al (1992), which has become the stepping stone for subsequent research in this area. On these very premises, research has focused mainly upon the magnitude of institutional herding, its stabilizing/destabilizing price-impact and whether its significance varies across different classifications of funds (origin, style) and stocks (size, industry). Institutional herding has been tested on the grounds of the Lakonishok et al (1992) measure in the US (Lakonishok et al. 1992; Grinblatt et al. 1996; Wermers, 1999), South Korea (Choe et al. 1999; Kim and Wei, 2002a; Kim and Wei, 2002b), Chile

(Olivares, 2005), Finland (Do et al, 2006), Germany (Oehler, 1998), Poland (Voronkova and Bohl, 2005), Portugal (Lobao and Serra, 2006), South Africa (Gilmour and Smit, 2002) and the UK (Wylie, 2005).

Although the above amount of research on institutional herding appears rather voluminous, it is interesting to note that little attention has thus far been devoted to the impact of various market conditions upon the herding of fund managers. Indeed, absent very few studies (Gilmour and Smit, 2002; Lobao and Serra, 2006), research regarding this issue appears to be notably limited.

To that end, we investigate institutional herding in the presence of a variety of herd-related market conditions in order to gauge whether the latter promote or inhibit its manifestation. More specifically, these conditions include: a) market-wide herding, b) trading volume, c) market volatility and d) market direction. The first of the four aforementioned features relates to herding at the market-level and is based upon recent research innovations (Hwang and Salmon, 2004) while the choice of the second one is based upon participation-based, Finance- and non-Finance-related, herding theories (more on those on Section 5.2.2.b). The third feature refers to the impact of volatility upon institutional herding and is based upon a variety of evidence, both theoretical as well as empirical regarding this relationship (see Section 5.2.2.c for more details); finally, the fourth feature is based upon analytical arguments as well as empirical findings from the realm of herding research (as we shall be discussing in Section 5.2.2.d) postulating that institutional herding can be affected by the direction of the

market. To the best of our knowledge, these market conditions have received very little or no attention as concerns their impact upon institutional herding⁹¹.

We conduct our research on the impact of the above market conditions upon institutional herding at the level of a market's index. An index constitutes a reference point (Huddart et al, 2002) for investors and as such it would be interesting to assess the impact of institutional herding upon it. What is more, we believe that, when investigating the impact of market conditions upon institutional herding, one needs to take the issue of *consistency* into consideration, in the sense that one should base the enumeration of both these conditions as well as institutional herding upon a common denominator. Given that relevant research appears not to have taken into account the issue of consistency⁹², the choice of studying institutional herding at the level of a specific index is made to tackle this problem.

As a result, we first calculate institutional herding on the premises of *the historical constituent stocks of a market's index*; for reasons of brevity, we shall be referring to this type of institutional herding throughout our work as "index-wide institutional herding". We then test for the impact of the aforementioned market conditions (market-wide herding, trading volume, volatility, market-direction) upon its presence. However, the important thing to note here is that these conditions correspond to the level of the index (i.e. they are: the herding

⁹¹ Gilmour and Smit (2002) address the impact of volatility upon institutional herding for South African unit trusts, while Lobao and Serra (2006) test-among other things-for the impact of market volatility and market direction upon the herding of Portuguese equity funds. It is our understanding that the impact of market-wide herding or the volume of trade upon institutional herding has never been tested.

⁹² Lobao and Serra (2006) test for herding on behalf of Portuguese equity fund managers on the basis of all stocks that were traded during any quarter by at least three funds in the Portuguese market. However, when assessing the impact of market direction and volatility upon institutional herding, they estimate the latter two on the basis of the PSI20 index, which is a selection-index, including the twenty most liquid stocks in that market.

towards the index-portfolio, the volume of the index, the index-volatility and the index-direction).

Our investigation is conducted on the basis of a unique database of monthly portfolio-holdings of Portuguese mutual funds obtained by the Portuguese Stock Exchange (Euronext Lisbon) for the 1997-2005 period. Our research contributes to the existing herding literature by providing useful insight into the impact of various market conditions upon the presence of institutional herding, an issue which has received rather scant attention in the herding literature. A key distinguishing feature of our research relates to the fact that it ties both institutional herding and the underlying market conditions to a specific index⁹³, thus ensuring the consistency of the investigation. We also contend that the study of institutional herding at the level of an index bears a certain interest from a practitioner's point of view as well. Since a number of derivative instruments are based upon market indices (e.g. index futures/options) the level of index-wide institutional herding may well constitute a useful element in the information-set of those trading in such derivatives, especially in light of the funds' leverage in the market.

The rest of the chapter is organized as follows: Section 5.2 includes a review of the literature pertaining to institutional herding, with special reference to the market conditions upon which its significance is tested. Section 5.3 presents the model used to estimate index-wide institutional herding while Section 5.4 presents a brief overview of the historical evolution of both the stock exchange (5.4.1) and

⁹³ Oehler (1998) provides evidence on the herding of German funds across the stocks of the DAX30-index; however, his research is neither exclusively index-based (he tests for herding on the premises of other factors as well (such as size and industry) nor does it take into account any market conditions.

the fund-industry (5.4.2) of the market under consideration (Portugal). Section 5.5 delineates the hypotheses relative to our study. Section 5.6 presents the data utilized (5.6.1), discusses the methodology employed (5.6.2) and presents some descriptive statistics (5.6.3). Section 5.7 presents the results (5.7.1) and discusses the empirical findings (5.7.2); Section 5.8 concludes.

5.2 Theoretical background

5.2.1 Institutional herding: Sources and Motivations

The case for institutional herding rests upon the premises of agents' relative homogeneity, since the possibility for observing commonality in behaviour is greater among market-agents who tend to face similar decision-problems (Bikhchandani and Sharma, 2001). Fund managers constitute a group of investors with rather similar backgrounds (in terms of education and professional qualifications) while their professional conduct is subject to a certain framework that defines the performance of their fiduciary duties (De Bondt and Teh, 1997). This homogeneity is expected to impact upon their trading decisions as it may render them prone (Lakonishok et al, 1992; Wermers, 1999) to the analysis of similar indicators, which may provide them with correlated signals. If so, fund managers may tend to interpret the latter in a parallel fashion, which in turn may lead them to exhibit similarities in their trading conduct, by selecting, for instance, stocks that have already been picked up by many of their peers (Lakonishok et al, 1992). The aforementioned conditions of relative homogeneity constitute the

pillars upon which the notion of institutional herding is founded. However, there also exist a multitude of factors that act as stimuli to its manifestation.

First of all, fund managers are essentially in the employment of investment companies and, as such, are subject to principal-agent considerations. As their performance is evaluated periodically on a relative basis, i.e. versus the performance of their peers, mostly those with similar (e.g. stocks, bonds, money-market, industry, foreign market/s etc) specializations (Ross et al, 1999), this creates a perceived “benchmark” upon which they may attempt to herd. As Scharfstein and Stein (1990) show, in an environment where the evaluation of the professionals’ ability is conducted on a relative basis, there is bound to exist some kind of uncertainty as to who is more and who is less able. The idea here is that under such circumstances, it may pay off to take advantage of this uncertainty by imitating the decisions of others, thus “jamming” the evaluation-process. “Bad” (i.e. less able) managers have an obvious incentive to copy the actions of their “good” (more able) peers, if this will help them appear as “better” professionals. “Good” managers, on the other hand, may choose to follow the investment-decisions of the majority of their peers, even if these are sub-optimal, in case “failing conventionally” is preferable to “succeeding unconventionally” (Keynes, 1936); such a situation may arise if the risk of failure (career-wise) exceeds the benefits of success by “going-it-alone”. Thus, as Lakonishok et al (1992) argue, there exists the issue of separating “luck from skill”, as telling the “good” from the “bad” managers in this context becomes hard to establish.

Reputational considerations are relevant to the aforementioned agency-concerns, as they may also encourage fund managers to herd. A professional who enjoys a strong reputation in his capacity has an incentive to imitate others in

order to preserve his reputation (Graham, 1999); this can be the case if the damage to his reputation by a potential failure outweighs the expected benefits from a potential success. If we assume that the well-reputed professionals are also the better-able ones (as it is hard to imagine how one's reputation would have grown in the absence of a distinctive ability), this may help explain the herding tendencies denoted previously with regards to the issue of ability. Managers with a weak reputation, however, may also resort to herding as a means of free-riding (Trueman, 1994) on the reputation of better-reputed colleagues (*reputational externality*).

The latter two motivations for institutional herding (agency-based and reputation-based) are directly associated with more general, information-based issues. After all, although the motive for a less able/reputed manager to herd may lie in his low ability/reputation, the underlying source of this herding propensity should probably be traced in the informational position of that manager. If one possesses no information, his information is of dubious quality, his information-processing abilities are inadequate, or he perceives others as better-informed, it is possible for him to free-ride on their information and discard his own. Under such circumstances, where such informational-payoffs are existent, fund managers may resort to herding (Devenow and Welch, 1996) in order to tackle their potential informational predicament.

A relevant case here involves informational cascades, where fund managers may ignore their private information and follow the actions of others, when they consider the information conveyed by others' actions to provide a useful set of information on its own (Banerjee, 1992; Bikhchandani et al, 1992). If so this is expected to lead to a poorer aggregation of information in the

marketplace and to negative informational externalities, as the private information of “cascading” investors is not revealed to others (since it is suppressed).

In view of the homogeneity mentioned above, another plausible case of institutional herding is the “spurious” one. Spurious herding involves a similarity in responses to similar decision problems following commonly observed signals (Bikhchandani and Sharma, 2001) and needs to be distinguished from the expressions of “intentional” herding depicted thus far. If a change in fundamentals (e.g. a drop in deposit rates) materializes, this may well have the potential of inducing fund managers to behave in a parallel fashion (e.g. possibly invest more in stocks).

We have, thus shown that institutional herding is a phenomenon that can be attributed to a multitude of factors. Our attention will now focus on institutional herding at the market-index level and the examination of those specific market conditions associated with it mentioned in the previous section.

5.2.2 Index-wide institutional herding

In this section, we will present the case for index-wide institutional herding by discussing in more detail those factors upon which its significance will be examined. These factors refer to properties of the market-index related to specific market conditions, which maintain a direct or indirect relationship to institutional herding and include market-wide herding, trading volume, market-volatility and market-direction.

5.2.2.a Market-wide herding

The impact of herding at the wider market-level upon institutional herding constitutes an issue which has never been touched upon in the literature related to herd behaviour. Given the absence of relevant evidence on the subject, we will attempt to approach it by invoking a combination of herd-related concepts: as will shortly become evident, the relationship between institutional and market-wide herding can assume both signs, each supported by different arguments.

We have noted in the introduction that institutional traders maintain a substantial leverage in the marketplace due to the amount of funds under their management (Wermers, 1999). As a result, it is reasonable to assume that any conjectural herding tendency on their behalf has the potential of inciting wider herding in the market, if other types of traders (e.g. retail ones) are lured into it and decide to join it. On the other hand, fund managers may exhibit more herding among themselves during periods of increased market-wide herding, in case they choose to ride on its waves with the intention of exploiting it (Hirshleifer and Teoh, 2003). The possibility for the latter is supported by both analytical (see, e.g. De Long et al, 1990; Andergassen, 2003) as well as empirical (Soros, 1987) works on rational speculative behaviour, which discuss how rational speculators may take advantage of the behavioural trading patterns of noise traders. What is more, if higher market-wide herding is associated with greater uncertainty in the marketplace, it may well make sense for fund managers to herd among themselves in order to resolve such a predicament.

However, fund managers may find herding among themselves more appealing during periods of relatively depressed market-wide herding, if lower

levels of market-wide herding are associated with higher “tranquility” in the marketplace. Such “tranquility” may be associated with a more definitive market-direction which fund managers can choose to herd upon. It may also be the case that relatively calm market conditions render the performance-benchmark of the relative evaluation of investment professionals more clear, thus easier to gauge-and, perhaps, follow.

As a result, there exist arguments in favour of both higher as well as lower levels of market-wide herding exerting a positive impact upon institutional herding; as this issue appears to be unresolved (and in view of the complete absence of relevant evidence in the herding literature), we propose testing for the hypothesis that *different levels of market-wide herding bear significantly different effects upon institutional herding at the index level*. For reasons of brevity, we shall be referring to market-wide herding at the index level as “index-wide market-herding”.

5.2.2.b Trading volume

The impact of a market’s trading activity upon institutional herding has not been addressed in the herding literature so far; thus, much like with the case for market-wide herding we discussed previously, there is complete absence of relevant evidence on this topic. Consequently, here again we will try to invoke relevant herd-related arguments to address this issue; our discussion here aims at demonstrating that the relationship between institutional herding and market-activity can assume multiple facets.

The arguments advocating a positive relationship between the market's turnover and institutional herding rest upon the nature of the "herd" as participation-based. Socio-psychological (Le Bon, 1895; 1910; 1912) as well as Finance-related theories (Banerjee, 1992; Bikhchandani et al, 1992) have shown that collective phenomena are the byproduct of imitation among people following interactive observation (Hirsheifer and Teoh, 2003) that leads to conformity towards a certain course of action. Thus, a herd's significance is a function of the accrued participation it attracts.

Let us now see how this translates in terms of institutional trading. If institutional traders do, indeed, herd, it is only reasonable to assume that the level of trading activity will exhibit a rise, more so, in view of the weight of their trades in the market. If fund managers herd on an existing trend, then, given their leverage, one would expect the level of market participation (and activity) to increase. If, on the other hand, fund managers "launch" a herd themselves and others follow suit, there will also exist a rise in market activity. Thus, either way, we would expect institutional herding to be more significant during periods characterized by an increased volume of trade.

However, herding is not the sole pattern of institutional trading that can lead to a rise in the market's turnover, since it may well be the case that funds engage themselves in intense trading (thus, boosting the overall market activity) without necessarily imitating each other. Kim and Wei (2002a) showed that certain categories of overseas funds engaged in heavy trading around the Asian Crisis in the South Korean market even though their herding levels were notably low.

As a result, a higher volume of trade can be associated with both higher as well as lower levels of institutional herding; as this issue appears to be unresolved, we propose testing for the hypothesis that *higher levels of market-turnover bear a significantly different effect upon institutional herding at the index level compared to lower ones.*

5.2.2.c Market volatility

The impact of volatility over institutional herding has thus far been the subject of very limited research in the herding literature. Gilmour and Smit (2002) and Lobao and Serra (2006) explored this issue for the South African and Portuguese markets respectively and documented evidence indicating that institutional herding tends to decline as the volatility of the market grows. Such findings may be justified through the fact that lower volatility may be associated with less turbulent market-conditions and, thus a more definitive market-direction upon which funds can herd. It may also be the case that less volatile market conditions render the benchmark upon which the relative performance of fund managers is evaluated less ambiguous and, hence, easier to follow. These arguments are essentially the same ones we employed before when discussing the impact of market-wide herding over institutional herding.

However, fund managers may choose to herd less during volatile periods due to information-based reasons as well. High volatility can be conducive to the informational efficiency of a market if it leads to a more rapid rate of incorporation of information into securities (Mayhew, 2000). Consequently, fund managers will be faced with an increased flow of information, thus having more

private signals at their disposal upon which they can trade; the above constitutes a plausible setting, since fund managers can be assumed to be better able to manage the information-processing in highly volatile markets (compared, for example, to retail traders) given their resources. In line with the above, several return-based herding studies (Christie and Huang, 1995; Gleason et al 2003; Gleason et al, 2004; Hwang and Salmon, 2004; Caparelli et al, 2004; Demirer and Kutan, 2005) document the absence of market-wide herding towards the market-index during extreme market periods.

Contrary to the above, there also exist arguments favoring a positive relationship between volatility and institutional herding. Volatility is associated with more uncertainty in the marketplace as wild price fluctuations may provide little indication of any definitive market direction and render the market more risky. Under those circumstances, the informational environment itself may grow more uncertain, given the volatility in the public pool of information and the associated difficulties in the latter's effective processing. Thus, institutional traders may choose to imitate their peers during periods of market turbulence in order to tackle this uncertainty rather than rely on the information available. A behaviour of the kind would be in line with the herding theories mentioned previously regarding the role of informational-payoffs (Devenow and Welch, 1996) and cascading (Banerjee, 1992; Bikhchandani et al, 1992) as possible motivations underlying institutional herding. Rising herding tendencies on behalf of institutional traders during periods characterized by high volatility have been documented by Kim and Wei (2002b) for the South Korean market during the Asian Crisis period.

As a result, there exist arguments in favour of both higher as well as lower levels of volatility exerting a positive impact upon institutional herding; given the unresolved nature of this issue, we propose testing for the hypothesis that *different levels of market-volatility bear significantly different effects upon institutional herding at the index level*.

5.2.2.d Market-direction

The manifestation of institutional herding can be affected by the directional state of the market, i.e. whether it rises or falls. The arguments here emanate mostly from agency-related theories of herding and imply the existence of differential effects of market-direction over institutional herding.

If the market goes well, then from a conformity point of view every manager would like to perform well, as a potential negative performance might cast a stigma over his perceived ability. Also, if everyone performs well in a euphoric market, a negative performance is not desirable as it makes a manager “stand out from the crowd”. Thus, as mentioned above (Scharfstein and Stein, 1990), “bad” managers would be prone to imitating their “good” peers during periods of market euphoria in order to free-ride on their ability and enhance their position by pretending to be “better” (or “less bad”). In this context, ill-reputed managers would also try to copy the decisions of their better-reputed colleagues, if this would confer a positive reputational externality onto them (Trueman, 1994). Thus, when the market performs well, fund managers might resort to herding if agency/reputational concerns prevail. In line with the above, Choe et al

(1999) found evidence indicating that foreign funds herded more among themselves prior to the outbreak of the Asian Crisis.

However, managers may also herd more among themselves when adverse market circumstances materialize, if they wish to minimize the perceived personal responsibility for their negative performance-and the accruing possible professional implications (Goodhart et al, 1998). Another reason related to institutional herding manifesting itself more boldly during market downturns is the propensity of fund managers towards making extensive use of positive-feedback-style strategies, such as portfolio insurance (Luskin, 1988) and stop-loss orders (Osler, 2002) in order to shield themselves against the realization of huge losses during market slumps. The employment of these hedging strategies by institutional investors may lead to their trades exhibiting higher correlation during market downturns, thus providing the impression of increased institutional herding. Kim and Wei (2002b) find higher herding levels on behalf of institutional traders in the South Korean market following the outbreak of the Asian Crisis compared to the period before it, while Lobao and Serra (2006) document more institutional herding in Portugal during market declines compared to market rises.

As a result, there exist arguments in favour of both rising as well as declining markets exerting a positive impact upon institutional herding: given the ambiguity surrounding the discussion of this issue, we propose testing for the hypothesis that *differential market-directions bear significantly different effects upon institutional herding at the index level.*



In view of our discussion above, we would like to recapitulate at this stage by drawing some attention to the fact that we test for institutional herding on the basis of premises upon which very little work has been undertaken before in the herding literature (see Section 5.1). More specifically, we test for institutional herding based upon market conditions (market-wide herding, volume of trade, volatility, market-direction) at the level of a market's index; we are not aware of any other institutional herding research having been conducted on those specific premises.

Our research contributes to existing empirical herding research by:

- Testing for institutional herding utilizing a unique database of institutional portfolio-holdings from the Portuguese Stock Exchange
- Providing extra insight into the manifestation of institutional herding by investigating its presence under various market conditions, an area which has received little attention in the herding literature.
- Developing a consistent framework for this investigation by establishing a common ground for the enumeration of both institutional herding as well as the relevant market conditions by conducting the research at the level of a specific market's index.

5.3 Measuring herding: Lakonishok et al (1992)

Lakonishok et al (1992) put forward the first measure designed to capture herding on the basis of funds' trades. In its original form, it is expressed as:

$$H_{i,t} = [| B_{i,t} / (B_{i,t} + S_{i,t}) - p_t |] - AF_{i,t} \quad (1)$$

where:

$B_{i,t}$ = the number of funds that increased their positions in stock i in period t (“buyers”)

$S_{i,t}$ = the number of funds that decreased their positions in stock i in period t (“sellers”)

$E(p_t)$ = the expected proportion of “buyers” in a period (t) relative to the total number of active funds under the null hypothesis of “no-herding”. It is calculated as the number of “buyers” relative to the total number of active funds across all stocks in period t and the notation p_t is often used instead. Its value remains constant for all stocks within the same period t , yet varies across periods. Note here that the term “active” refers to those funds that changed their positions in a stock and does not include the funds whose positions remained unchanged⁹⁴.

$AF_{i,t}$ = represents the adjustment factor designed to capture the random variations of the $[|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|]$ around p_t and is calculated for each stock i in each month t , under the assumption that $B_{i,t}$ follows a binomial distribution with probability of success $p = p_t$. The adjustment factor also helps to prevent the bias in the estimation of $[|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|]$ potentially arising in case a stock is traded by a small number of funds. $AF_{i,t}$ declines in value as the number of funds active in a stock rises. To illustrate this we use the approach of Jones et al (1999) by employing some numerical examples. Let us for a moment assume that $p_t = 0.80$, i.e. that, on average, 80 percent of all active funds were buyers across

⁹⁴ This raises, of course, the issue of whether a zero change in a fund's position is suggestive of trading inertia on behalf of that fund or a data-induced illusion. If quarterly data, for example, indicates that a fund's position remained unchanged, this might well be the outcome of a number of purchases and sales that resulted in the fund maintaining an identical position in that stock.

all stocks in period t and let us also assume that one of the stocks in that period is traded by five funds. The $AF_{i,t}$ for that stock is then computed as follows:

No. of Buyers	(1) Binomial Probability $\frac{n! \cdot (p)^k \cdot (1-p)^{n-k}}{[(n-k)! \cdot k!]}$	(2) Expected Value $ B_{i,t} / (B_{i,t} + S_{i,t}) - p_t $	Product (1)x(2)
0	0.00032	0.8	0.000256
1	0.0064	0.6	0.00384
2	0.0512	0.4	0.02048
3	0.2048	0.2	0.04096
4	0.4096	0	0
5	0.32768	0.2	0.065536

Summing up the results from the “Product”-column (in line with Jones et al, 1999) we obtain $AF_{i,t} = 0.131072$. Thus, the possible herding measures for a stock with five funds active in it during period i, are:

No. of Buyers	$H_{i,t} = B_{i,t} / (B_{i,t} + S_{i,t}) - p_t - AF_{i,t}$
0	$0.8 - 0.131072 = 0.668928$
1	$0.6 - 0.131072 = 0.468928$
2	$0.4 - 0.131072 = 0.268928$
3	$0.2 - 0.131072 = 0.068928$
4	$0 - 0.131072 = -0.13107$
5	$0.2 - 0.131072 = 0.068928$

To illustrate that $AF_{i,t}$ declines as the number of active traders rises, let us repeat the same example by assuming that the number of active funds in that stock is now seven.

<i>No. of Buyers</i>	<i>(1) Binomial Probability $\frac{n! \cdot (p)^k \cdot (1-p)^{n-k}}{[(n-k)! \cdot k!]}$</i>	<i>(2) Expected Value $B_{i,t} / (B_{i,t} + S_{i,t}) - p_t$</i>	<i>Product (1)x(2)</i>
0	0.0000128	0.8	0.00001024
1	0.0003584	0.657142857	0.00023552
2	0.0043008	0.514285714	0.00221184
3	0.028672	0.371428571	0.0106496
4	0.114688	0.228571429	0.0262144
5	0.2752512	0.085714286	0.02359296
6	0.3670016	0.057142857	0.02097152
7	0.2097152	0.2	0.04194304

Summing up the “Product”-column results we obtain $AF_{i,t} = 0.12582912$, which is less than the value we obtained for it previously when assuming five active funds.

It is important to note that the Lakonishok et al (1992) measure of herding as depicted above indicates the tendency of investors to trade a certain stock towards a certain direction more than random, independent trading would otherwise imply. Correlation is a quintessential element of herding, as the latter cannot materialize in the absence of the convergence of trades; however, correlation can exist independently of herding, as it may well be due to “spurious” herding, e.g. traders jointly responding to commonly observed signals, as noted previously. Thus, it would, perhaps, be more accurate to claim that the Lakonishok et al (1992) measure captures the propensity of institutional traders towards correlated trading in a certain direction rather than actual herding on their behalf as it is not possible to establish the presence of intent or spuriousness (in line with the distinction offered by Bikhchandani and Sharma, 2001) in the results of this measure.

The Lakonishok et al (1992) measure has been employed both in its original as well as modified forms in a variety of markets, both developed as well as developing. For illustration purposes, Table 5.1 presents the results in chronological order on the mean herding measure for institutional traders from studies using the Lakonishok et al (1992) measure.

5.4 The market environment of our study: Portugal

5.4.1 The Portuguese Stock Exchange: a short historical overview

Following an initial period of boom (culminating during the latter half of the 1980s) and bust (early 1990s) after its official reopening in early 1977, the Portuguese Stock Exchange embarked onto a period of growth towards maturity during the mid-1990s. During this period the country entered into a booming cycle with foreign direct investment, exports and GDP documenting a sharp increase. Privatizations, namely of blue-chip state-owned firms⁹⁵ were also very intense during this period. On June 1996, the Derivatives' Exchange in Porto was officially launched, thus providing the opportunity for increased market participation through derivative instruments. In December 1997, the Portuguese stock exchange was upgraded by Morgan Stanley to "mature" and 19 of its companies were listed in the Dow Jones indices. Finally, in 1998, it was publicly announced that Portugal would be joining the third stage of the European Monetary Union. Overall, this sequence of favourable economic events led to a substantial increase in trading activity while the market index rose by 270% (January 1996 – April 1998).

⁹⁵ Examples include "Brisa", "Cimpor", "EDP" and "Portugal Telecom".

Table 5.1: Institutional herding literature on the premises of the Lakonishok et al (1992) measure

<i>Study</i>	<i>Market</i>	<i>Sample window</i>	<i>Underlying object of herding investigation</i>	<i>Data-frequency</i>	<i>Mean herding measure for institutional traders</i>
Lakonishok et al (1992)	US	1985-1989	Tax-exempt pension funds	Quarterly	0.027
Grinblatt et al (1996)	US	1/1/1975-31/12/1984	Mutual funds	Quarterly	0.025
Oehler (1998)	Germany	1988 to mid-1993	Local equity funds	Semi-annual	0.8
Choe et al (1999)	South Korea	2/12/1996-27/12/1997	Overseas institutional traders	Daily	0.035
Jones et al (1999)	US	1984-1993	Mutual funds	Quarterly	0.016
Wermers (1999)	US	1/1/1975-1/1/1994	All equity-holding mutual funds	Quarterly	0.034
Kim and Wei (2002)	South Korea	1/1/1997-30/6/1998	All investor-types	Monthly	0.05-0.06
Kim and Wei (2002)	South Korea	1/1/1997-30/6/1998	Overseas institutional traders	Monthly	≤ 0.09
Gilmour and Smit (2002)	South Africa	1/12/1991-1/9/1999	Local unit trusts	Quarterly	0.07-0.08
Olivares (2005)	Chile	June 1997-December 2001	Local pension funds	Monthly	0.018
Voronkova and Bohl (2005)	Poland	1999-2002	Local pension funds	Annually	0.226
Wylie (2005)	UK	1/1/1987-31/12/1993	Local equity mutual funds	Semi-annually	0.026
Lobao and Serra (2006)	Portugal	1998-2000	Local equity funds	Quarterly	0.1138
Do et al (2006)	Finland	March 1995-May 2004	All investor-types	Monthly	0.0835

Between the end of 1998 and 2002, the Russian/Asian Crises and the Dotcom-bubble brought about higher levels of volatility to the Portuguese stock exchange. In the end of 1998, the Russian/Asian crises created instability that later spread to other developing economies, including Brazil (a preferential destination for Portuguese foreign direct investment). That instability was particularly felt in the Portuguese stock exchange between the last quarter of 1998 and the end of 1999, with the decrease of the market index pointing towards a forthcoming recession.

However, in the first quarter of year 2000, there was a significant positive inversion in the market trend. This fact was mainly due to a late impact of the Dotcom-bubble in Portugal (Balbina and Martins, 2002). During the last quarter of 1999 and early 2000, there was a rise in the initial public offerings of IT-companies⁹⁶ accompanied by a rally in their prices (Sousa, 2002). This rally came to an abrupt halt during the first quarter of year 2000, following the slump observed in the NASDAQ. After March 2000, the Portuguese market experienced a prolonged period of free-fall that lasted for over two years⁹⁷. In an effort to boost trading activity, the Lisbon Stock Exchange joined the Euronext-platform in 2002; however, the market exhibited signs of only moderate increase ever since with economic recovery still hampered by the country's slow convergence to EU-requirements (especially those regarding reforms in the public sector and the Stability and Growth Pact).

⁹⁶ Examples include "PT Multimedia", "PT Multimedia.Com", "Novabase", "Impresa" and "Sonae.Com"

⁹⁷ Our presentation in this section suggests that the Portuguese market underwent a series of booms and busts during our sample period and we expect the above to bear some influence upon the empirical part (i.e. institutional herding results) of this chapter.

5.4.2 The Portuguese funds' industry

The evolution of the Portuguese mutual funds' industry can be traced back to the mid-1980s, in the aftermath of the country's accession to the European Union. During the 1990s, the sector experienced rapid levels of growth that culminated during the "boom-bust" period between 1995 and 1999 into a large increase both in terms of the number of funds that were launched as well as in terms of the amounts of capital under their management. The instability reigning the market after 1999 and the concomitant market crises (local and global) created uncertainty in the market environment that led to changes in the mutual fund industry, which underwent a certain consolidation between 2000 and 2002 (Leite and Cortez, 2006). Table 5.2 provides us with the picture of the evolution of the mutual funds' industry in Portugal since its inception⁹⁸.

A fundamental feature of the Portuguese funds' industry is its high levels of concentration as Leite and Cortez (2006)⁹⁹ and Lobao and Serra (2006)¹⁰⁰ note. Since the Portuguese funds' sector is mostly under the management of a few large universal banking groups (Alves and Mendes, 2004; Leite and Cortez, 2006; Alves and Mendes, 2006), it is reasonable to expect that the fortunes of the latter bear a knock-on effect upon the development of the funds' industry. An example here relates to the mergers between mutual funds during the 2000-2002 period which followed the concentration of the banking sector during the same period. By May 2006, there existed 251 mutual funds managed by 15 asset management

⁹⁸ Source: CMVM, 2002

⁹⁹ According to Leite and Cortez (2006), the five largest asset management companies maintained approximately 91% of the total net asset value of funds in the market by year-end 2004.

¹⁰⁰ According to Lobao and Serra (2006), the three largest asset management companies maintained approximately 69% of the total net asset value of funds in the market by mid-2001.

companies; the total value of their assets equalled approximately 28 ½ billion euros¹⁰¹.

Table 5.2: Evolution of the Portuguese mutual funds' industry

Year	Number of funds	Net Asset Value (million €)
June 1986	1	51
Dec 1987	5	251
Dec 1988	7	205
Dec 1989	24	1,003
Dec 1990	51	1,895
Dec 1991	82	4,305
Dec 1992	98	5,791
Dec 1993	109	8,260
Dec 1994	126	10,260
Dec 1995	150	10,639
Dec 1996	182	13,208
Dec 1997	204	19,615
Dec 1998	246	23,955
Dec 1999	272	24,087
Dec 2000	260	21,558
Dec 2001	262	21,266
Dec 2002	228	20,377
Dec 2003	215	22,850
Dec 2004	224	24,415
Dec 2005	242	28,290
May 2006	251	28,469

Source: CMVM¹⁰²

5.5 Hypotheses

We will now present our hypotheses on the basis of our previous discussion in Section 5.2.2.

¹⁰¹ Source: <http://www.cmvm.pt>
¹⁰² Securities' Exchange Commision of Portugal.

Hypothesis 1: Different levels of market-wide herding bear significantly different effects upon institutional herding at the index level

Hypothesis 2: Higher levels of market-turnover bear a significantly different effect upon institutional herding at the index level compared to lower ones

Hypothesis 3: Different levels of market-volatility bear significantly different effects upon institutional herding at the index level

Hypothesis 4: Differential market-directions bear significantly different effects upon institutional herding at the index level

5.6 Data and Methodology

5.6.1 Data

We utilize a database of institutional portfolio-holdings obtained from the Portuguese Stock Exchange (Euronext Lisbon). The database includes the monthly portfolio-structures of all funds investing in the Portuguese market between October 1995 and March 2006 and provides us with the following information: a code corresponding to each fund, a code corresponding to the managing company of each fund, date (month), a code corresponding to the fund-type (i.e. equity, fixed-income et al), a code corresponding to the type of the asset included in a fund's portfolio (i.e. stock, bond et al), a code for each asset, the name of each asset, the currency into which the position of the fund in an asset is expressed (Portuguese Escudo prior to 1/1/1999, Euro afterwards), the currency exchange-rate (Euro-Escudo, for conversion purposes), the turnover in shares, the market in which the asset is traded (in case a fund holds stocks listed outside

Portugal) and the turnover-value. Due to the absence of data for several months during 1995-96 as well as 2006, we chose the January 1997 - December 2005 period in order to measure institutional herding.

We estimate index-wide institutional herding on the premises of the PSI20-index, which includes the twenty most liquid stocks in the Portuguese Main market. The latter also maintains the PSIGeral-index, which accommodates all stocks meeting the criteria to qualify for listing on the Main market. The choice of measuring herding on the basis of the PSI20 and not the PSIGeral is founded upon the availability of historical lists of the constituent stocks of those indices. We did not manage to obtain historical constituents' lists for the PSIGeral during the 1997-2005 period; we, therefore, used the historical constituent lists of the PSI20-index. PSI20-lists are available online¹⁰³ for the period beginning from the inception of the index (1/1/1993) up to year-end 2001, while the lists for the 2002-2005 period were obtained from the Euronext Lisbon. Given the limited number of stocks traded on the Portuguese Main Market (the PSIGeral has included around 50 stocks¹⁰⁴ in its ranks during the past decade or so) and the proportion of total market capitalization it represents (close to 90%, according to Balbina and Martins (2002)), we contend that the choice of the PSI20 provides us with a good benchmark of the market's activity.

To estimate index-wide market-herding (Hypothesis 1), we use the daily closing prices of both the PSI20-index as well as its historical constituent stocks during the January 1997 – December 2005 period, while to proxy for the risk-free rate (to estimate excess returns-see next subsection on Methodology) we utilize

¹⁰³ <http://www.euronext.pt/bvlp/start.jsp?lang=en&op=mercados>

¹⁰⁴ On the 24th of July 2006, the total number of stocks included in the PSI Geral equaled 53.

the 3-month deposit-rate (up to 31/12/1998) and the 3-month Euribor (after 1/1/1999). All data were obtained from DataStream. Finally, to test for the association between index-wide institutional herding and trading volume (Hypothesis 2), we use data on the turnover-value of the PSI20 obtained from the Euronext Lisbon.

5.6.2 Methodology

We measure institutional herding in the Portuguese market at the level of the PSI20-index (“index-wide institutional herding”) using the Lakonishok et al (1992) measure delineated in Section 5.3. Each month, we calculate the number of “buyers” and “sellers” for each of the constituent stocks of the PSI20 index and then calculate the p_i (average proportion of “buyers”) and the adjustment factor. The measure for institutional herding for each month is given by averaging the herding measures across all stocks included in the index in that month.

An important issue here concerns the minimum number of funds required to be active in a stock in order to measure funds’ herding upon it. This threshold varies across institutional herding studies contingent upon the sample-properties and upon certain predilections as to what minimum number of active funds constitutes a “herd”. Here we test for the significance of institutional herding at the level of the PSI20-index, which maintains exact constituent lists and it is on the basis of those lists that herding is estimated. If we impose arbitrary stock-selection criteria for herd-estimation (e.g. take into consideration only those stocks traded by, say, five, ten or twenty funds in each month), we run the risk of biasing our results. This is because the anticipated exclusion of some stocks will

essentially imply that the stocks used to estimate herding each month will be a fraction of the actual constituents of the index. Thus, instead of estimating institutional herding at the level of the PSI20-index, we would probably be getting a herding-estimate for a subset of PSI20-stocks.

We choose to work each month with those constituent stocks of the PSI20 that are traded by, at least, two funds. As a result, any stock traded in a month by a single fund or no funds will be erased from the estimations of herding for that month. Even though two active funds may not produce a notable “herd”, we use this minimum threshold in order to account even for the most extreme case of herding (two funds, one potentially following the other).

To estimate index-wide market-herding (Hypothesis 1), we employ the model developed by Hwang and Salmon (2004) which we delineated in the previous chapter. Regarding the volume of trade used to test for Hypothesis 2, it is calculated at the monthly level using the monthly aggregate of the daily data of the turnover-value of the PSI20. Regarding the market volatility used to test for Hypothesis 3 (i.e. the impact of volatility of the market-index upon the significance of index-wide institutional herding) it is calculated using squared daily returns of the PSI20 at the monthly level according to the methodology proposed by Schwert (1989). Regarding, finally, the index returns (Hypothesis 4) these are estimated at the monthly level using the average of the daily returns of the PSI20-index for each month. To calculate these daily returns, we assume the percentage difference of the natural logarithms of the PSI20 closing prices.

5.6.3 Descriptive Statistics

5.6.3.a Index-wide institutional herding

Our sample includes all historical constituent stocks of the PSI20-index during the January 1997 – December 2005 period. Although the name of the index implies that the number of stocks each month is equal to twenty, this number does not necessarily hold for each month in our herding estimations. This is due to the cut-off threshold requiring at least two funds trading in a stock each month: a stock may not be satisfying this threshold as it may be traded by one fund-or none. Note also, that we only take into account the “active” funds, namely those whose position in a stock has changed (upwards or downwards) during a month.

Given the aforementioned sample-window, we estimate index-wide institutional herding using the Lakonishok et al (1992) model for 108 months (9 years times 12 months each). Table 5.3 presents some descriptive statistics regarding the monthly portfolio-holdings for our database. For 64 out of those 108 months, the herding measure is estimated on the basis of all twenty stocks of the PSI20, while for 39 months for nineteen stocks. As a result, for 95% of the sample (103 out of 108 months) the estimations are conducted on the basis of, at least 95% of the historical constituent stocks of the index. This, in turn implies that the data at hand are providing us with the opportunity of measuring institutional herding on the premises of the exact historical composition of the PSI20.

The estimation of institutional herding on the premises of the historical constituent stocks of the PSI20-index yielded a total number of sixty mutual funds (Portuguese, in their supreme majority) active in the PSI20-stocks during the

1997-2005 period with the average number of funds trading (i.e. buying or selling) a stock in a given month being equal to 23.4.

5.6.3.b Index-wide market-herding

Table 5.4 presents some statistics related to the estimated logarithmic cross-sectional standard deviation of the betas of the PSI20-portfolio. As indicated by the table, the logarithmic cross-sectional standard deviation of the betas exhibits insignificant values of both skewness and kurtosis, while the Jarque-Bera statistic does not indicate departures from normality. Therefore, the state-space model of Hwang and Salmon (2004) described previously can be legitimately estimated using the Kalman filter on the premises of the PSI20-index for our sample-period.

5.7 Results-Discussion

5.7.1 Results

Table 5.5 presents our main results from the herding estimations. The mean index-wide institutional herding measure is computed as follows: first we average the herding measures of all constituent stocks of the PSI20 for each month, in order to obtain the monthly measures of herding and then we average

Table 5.3: Descriptive properties of the 1997-2005 portfolio-holdings database

<i>a) PSI20-composition and Euronext-database coverage</i>	
Number of PSI20-constituent stocks with two or more funds trading	Number of months
20	64
19	39
18	2
17	2
16	1
<i>b) Funds' properties</i>	
Total number	60
Average number of active funds per stock per month	23.42553
Median number of active funds per stock per month	22.2

Table 5.4: Properties of the logarithmic cross-sectional standard deviation of the betas for the Hwang and Salmon (2004) measure

	Logarithmic cross-sectional standard deviation of OLS betas
<i>Mean</i>	-0.2187103178
<i>Standard Deviation</i>	0.1281628386
<i>Skewness</i>	-0.38838
<i>Kurtosis</i>	0.00549
<i>Jarque-Bera</i>	2.71527

the latter to get the full-period, mean index-wide institutional herding measure, which, as our results indicate, is found to equal 0.1282 (or 12.82%) with a median of 0.13. These results imply that if 100 funds were active in an average stock of the PSI20, about 13 more of them trade on the same side (buy/sell) than would otherwise be expected under the null hypothesis of no-herding. In other words, about 63% (50% under the null of no-herding plus the extra 12.82% mean herding measure from our results) of the active institutional investors in PSI20-stocks traded in one direction in any single month, on average, and the remaining 37% in the opposite one. These results are in line with similar results documented in other markets, as indicated by Table 5.1; in most cases, the mean institutional herding measure was found to be between 0.01 and 0.2.

Having presented the overall index-wide institutional herding picture for our full sample-period, we now turn to the results regarding our hypotheses.

Table 5.5: Overall herding

Herding statistics for all stock-months (full sample period: 1/1/1997-31/12/2005). The herding statistic for a given stock in a given month is defined as: $H_{i,t} = [|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|] - AF_{i,t}$, where $B_{i,t}$ is the number of funds that increased their positions in stock i in period t (“buyers”), $S_{i,t}$ is the number of funds that decreased their positions in stock i in period t (“sellers”), p_t is the expected proportion of “buyers” in a period (t) relative to the total number of active funds and $AF_{i,t}$ is an adjustment factor designed to capture the random variations of the $[|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|]$ around p_t . The herding measure is calculated for each stock in each month, averaged across each month and then averaged across all months. Standard errors are in brackets. Note that: * = significance at the 10% level, ** = significance at the 5% level, *** = significance at the 1% level.

Mean herding measure for full-sample (1/1/1997-31/12/2005)	
Mean	0.1282 (0.0047)***
Median	0.13

5.7.1.a Index-wide institutional herding and index-wide market-herding

In hypothesis 1 we stated that different levels of market-herding would be expected to bear significantly different effects over institutional herding at the index-level. Table 5.6 presents the results from the Hwang and Salmon (2004) estimations regarding index-wide market-herding. According to these results, there appears to exist significant index-wide market-herding at the PSI20-level as both ϕ_m and $\sigma_{m,\eta}$ (the standard deviation of η_{mt}) are statistically significant (5% level). The bottom row of Table 5.6 provides us with the signal-proportion value, which according to Hwang and Salmon (2004) indicates what proportion of the variability of the logarithmic cross-sectional standard deviation of the betas is explained by herding. The signal-proportion is estimated by dividing the $\sigma_{m,\eta}$ by the time series standard deviation of the logarithmic cross-sectional standard deviation of the betas and, as Hwang and Salmon (2004) showed empirically in their paper, the bigger the value of the signal-to-noise ratio, the less smooth the evolution of herding over time. Our results show us that the signal-proportion value equals approximately 20%, a figure relatively small (much smaller than the corresponding ones in Hwang and Salmon (2004))¹⁰⁵, thus suggesting a smooth evolution of herding towards the PSI20 during the 1997-2005 period. To illustrate the herding course, we first extract the h_{mt} as described in chapter Four (according to equation (6) there, $h_{mt} = 1 - \exp(-H_{mt})$) and then plot it in Figure 5.1.

¹⁰⁵ Around 40% for both the US and South Korean markets.

Figure 5.1 provides us with a graph of the course of herding (thin line) as well as the PSI20 index (thick line). As the graph indicates, herding towards the PSI20 was on the ascending from the beginning of our sample period (January 1997) until November 1998 and then started dwindling towards lower levels. Given our discussion of the recent historical evolution of the Portuguese market, we can argue that herding appears to be rising as the market rallied throughout 1997 and continued to rise in the aftermath of its drop (April 1998) until it hit a bottom (November 1998). Following that point, herding exhibited a free-fall that lasted until 2001 and then presented itself with a multiplicity of fluctuations until year-end 2005.

To test whether index-wide institutional herding is higher or lower during periods of higher/lower index-wide market-herding, we first calculate index-wide institutional herding for periods of rising and for periods of declining index-wide market-herding. The rises/declines of index-wide market-herding are estimated here on a month-to-month basis using the h_{mt} -series.

Table 5.6: Herding results from the Hwang and Salmon (2004) measure

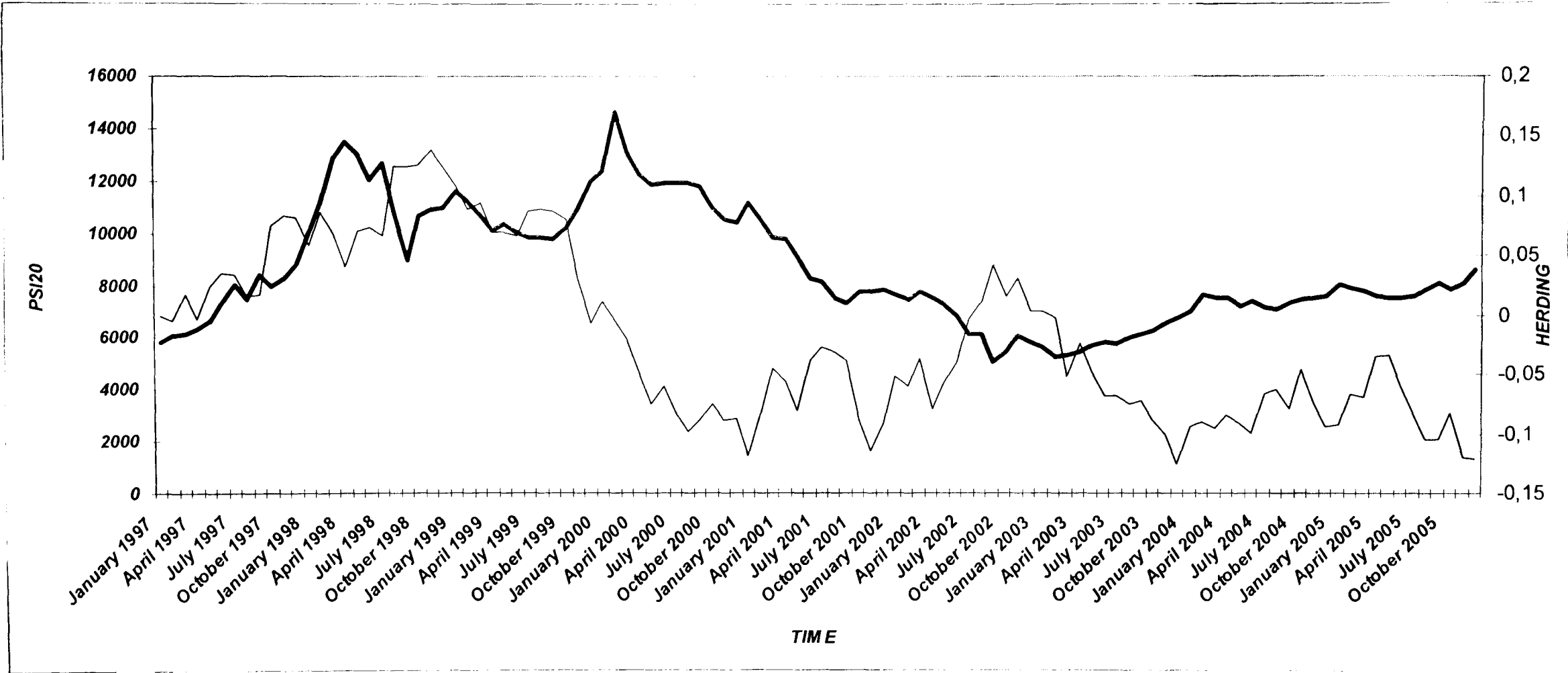
$$\log [Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt}, \quad \upsilon_{mt} \sim iid(0, \sigma_{m,\upsilon}^2)$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}, \quad \eta_{mt} \sim iid(0, \sigma_{m,\eta}^2)$$

Variable	Estimates
μ_m	-0.241053538 (0.040827366)***
ϕ_m	0.963013736 (0.031951560)***
$\sigma_{m,\upsilon}$	0.025643225 (0.000326467)**
$\sigma_{m,\eta}$	0.097473648 (0.001434830)***
$\sigma_{m,\eta} / \text{S.D. (log-CXB)}$	0.200083156

(* = 10% sign. Level, ** = 5% sign. Level, *** = 1% sign. Level). Parentheses include the standard errors of the estimates; sample period: 1/1/1997-31/12/2005.

Figure 5.1: Market-wide herding towards the PSI20 during the 1997-2005 period



PSI20 = thick line
Herding = thin line

Table 5.7 shows us that index-wide institutional herding is significant (1% level) irrespective of the state of index-wide market-herding. The mean index-wide institutional herding measure for periods of rising index-wide market-herding (0.1218) is lower compared to the one during periods of declining index-wide market-herding (0.1351) indicating that funds tend to herd less when there is a rise in herding in the market towards the PSI20. The levels of index-wide institutional herding between periods of rising and periods of declining index-wide market-herding were found to be significantly different (10% level); Table 5.7 presents the results from the relevant Wald-tests.

We then partitioned index-wide market-herding into three subgroups based upon its level (“high”, “mid”, “low”) and calculated index-wide institutional herding for each subgroup¹⁰⁶. Results in Table 5.7 indicate that index-wide institutional herding was found again to be significant (1% level) irrespective of the state of index-wide market-herding, although index-wide institutional herding assumes its lowest value when index-wide market-herding at the PSI20-level is high. However, the levels of index-wide institutional herding across these three subgroups were found to be insignificantly different from each other (see the Wald-tests’ results in Table 5.7).

Thus, these results seem to suggest that index-wide institutional herding appears to be statistically significant irrespective of the state of index-wide market-herding. However, index-wide institutional herding is found to be higher at decreasing as opposed to increasing index-wide market herding levels; having said that, though, the difference of the size of index-wide institutional herding

¹⁰⁶ *All three subgroups are of equal size, i.e. upper, mid- and lower third of index-wide market herding.*

between those levels is not always found to be significant. As a result, these results appear to provide insufficient support for our first hypothesis, namely, that different levels of market-herding bear significantly different effects over institutional herding at the index-level.

5.7.1.b Index-wide institutional herding and index-wide trading volume

In hypothesis 2 we proposed that higher trading volume would be expected to bear a significantly different effect over institutional herding at the index-level compared to lower trading volume. We calculate the volume of trade using the turnover-value at the monthly frequency in line with what we mentioned in Section 5.6.2. To test our hypothesis, we first measured index-wide institutional herding for periods of rising and for periods of declining turnover-value. The rises/declines are estimated here on a month-to-month basis. Table 5.8 shows us that index-wide institutional herding is significant (1% level) irrespective of the state of index-wide trading volume. The mean index-wide institutional herding measure for periods of rising index-wide trading volume is lower compared to periods of declining index-wide trading volume, thus indicating that funds tend to herd less when there is a rise in the trading activity towards the PSI20-stocks.

The difference between the levels of index-wide institutional herding between periods of rising and periods of declining index-wide trading volume was found to be insignificant, as the results from the relevant Wald-tests in Table 5.8 indicate.

We then partitioned index-wide trading volume into three subgroups based upon its level (“high”, “mid”, “low”)¹⁰⁷ and calculated index-wide institutional herding for each subgroup. Results in Table 5.8 indicate that index-wide institutional herding assumes its lowest value when index-wide trading volume is high, thus indicating that funds tend to herd less when the PSI20 experiences high trading activity. Again here, index-wide institutional herding was found to be significant (1% level) irrespective of the levels of the PSI20-volume. To assess the difference between the levels of index-wide institutional herding among the three subgroups we performed Wald-tests; results demonstrated that this difference was insignificant, as Table 5.8 indicates. Thus, these results seem to suggest that index-wide institutional herding appears to be statistically significant irrespective of the state of index-wide trading.

Thus, these results seem to suggest that index-wide institutional herding appears to be statistically significant irrespective of the state of index-wide trading volume, with its levels declining during periods of increasing trading activity. However, the difference in the size of index-wide institutional herding between periods of increasing and decreasing index-wide trading volume appears to be insignificant. Consequently, these results seem to reject our second hypothesis, namely that higher trading volume bears a significantly different effect over institutional herding at the index-level compared to lower trading volume.

¹⁰⁷ *All three subgroups are of equal size, i.e. upper, mid- and lower third of index-wide trading volume.*

Table 5.7: Index-wide institutional herding and index-wide market-herding

Herding statistics for all stock-months (full sample period: 1/1/1997-31/12/2005). The herding statistic for a given stock in a given month is defined as: $H_{i,t} = [|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|] - AF_{i,t}$, where $B_{i,t}$ is the number of funds that increased their positions in stock i in period t ("buyers"), $S_{i,t}$ is the number of funds that decreased their positions in stock i in period t ("sellers"), p_t is the expected proportion of "buyers" in a period (t) relative to the total number of active funds and $AF_{i,t}$ is an adjustment factor designed to capture the random variations of the $[|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|]$ around p_t . The herding measure is calculated for each stock in each month, averaged across each month and then averaged across all months, according to the grouping for each test. Standard errors are in brackets. Note that: * = significance at the 10% level, ** = significance at the 5% level, *** = significance at the 1% level.

a) Index-wide institutional herding during periods of rising and declining index-wide market-herding						
	Rising	Declining		Difference (rising – declining)		
Mean index-wide institutional herding measure	0.1218 (0.0076)***	0.1351 (0.0059)***		-0.0163 (0.0094)*		
b) Index-wide institutional herding across different levels of index-wide market-herding						
	High	Mid	Low	Difference (high – low)	Difference (high – mid)	Difference (low – mid)
Mean index-wide institutional herding measure	0.1178 (0.0085)***	0.1322 (0.0082)***	0.1346 (0.008)***	-0.0168 (0.0151)	-0.0144 (0.0125)	0.0024 (0.03)

Table 5.8: Index-wide institutional herding and index-wide trading volume

Herding statistics for all stock-months (full sample period: 1/1/1997-31/12/2005). The herding statistic for a given stock in a given month is defined as: $II_{i,t} = \left| \frac{B_{i,t}}{B_{i,t} + S_{i,t}} - p_t \right| - AF_{i,t}$, where $B_{i,t}$ is the number of funds that increased their positions in stock i in period t ("buyers"), $S_{i,t}$ is the number of funds that decreased their positions in stock i in period t ("sellers"), p_t is the expected proportion of "buyers" in a period (t) relative to the total number of active funds and $AF_{i,t}$ is an adjustment factor designed to capture the random variations of the $\left| \frac{B_{i,t}}{B_{i,t} + S_{i,t}} - p_t \right|$ around p_t . The herding measure is calculated for each stock in each month, averaged across each month and then averaged across all months, according to the grouping for each test. Standard errors are in brackets. Note that: * = significance at the 10% level, ** = significance at the 5% level, *** = significance at the 1% level.

<i>a) Index-wide institutional herding during periods of rising and declining index-wide trading volume</i>						
	Rising	Declining		Difference (rising – declining)		
Mean index-wide institutional herding measure	0.1289 (0.0071)***	0.1291 (0.0064)***		-0.0002 (0.01)		
<i>b) Index-wide institutional herding across different levels of index-wide trading volume</i>						
	High	Mid	Low	Difference (high – low)	Difference (high – mid)	Difference (low – mid)
Mean index-wide institutional herding measure	0.1255 (0.0084)***	0.1295 (0.0081)***	0.1296 (0.0084)***	-0.0041 (0.12)	-0.004 (0.117)	0.0001 (0.01)

5.7.1.c Index-wide institutional herding and index-volatility

In hypothesis 3 we stated that different levels of market volatility would be expected to bear significantly different effects over institutional herding at the index-level. To test whether this is the case, we first measured index-wide institutional herding for periods of rising and for periods of declining index-volatility, the latter calculated at the monthly frequency in line with what we mentioned in Section 5.6.2. The rises/declines of index-volatility are estimated here on a month-to-month basis. Table 5.9 shows us that index-wide institutional herding is significant (1% level) irrespective of the state of index-volatility. The mean index-wide institutional herding measure for periods of rising index-volatility (0.1126) is lower compared to periods of declining index-volatility (0.1424) indicating that funds tend to herd less when there is a rise in the volatility of the PSI20. The difference between the levels of index-wide institutional herding between periods of rising and periods of declining index-volatility was found to be significant at the 1% level, as the results from the Wald-tests in Table 5.9 show.

We then partitioned index-volatility into three subgroups on the basis of its level (“high”, “mid”, “low”)¹⁰⁸ and re-calculated index-wide institutional herding for each subgroup. Results in Table 5.9 indicate that index-wide institutional herding assumes its highest value (0.1492) when index-volatility is low. Again here, index-wide institutional herding was found to be significant (1% level) irrespective of the state of index-volatility.

¹⁰⁸ *All three subgroups are of equal size, i.e. upper, mid- and lower third of index volatility.*

Using Wald-tests we found the difference between the levels of index-wide institutional herding during periods of “low” index-volatility and during periods of “high”/“mid” index-volatility to be significant at the 5% level, thus indicating that index-wide institutional herding is significantly higher when the PSI20 is least volatile.

A number of studies (Christie and Huang, 1995; Gleason et al 2003; Gleason et al, 2004; Hwang and Salmon, 2004; Caparelli et al, 2004; Demirer and Kutan, 2005) have unveiled the absence of herding towards the market-index during periods of extreme market returns, the latter defined as lying over a single standard deviation from the average return of the index during a period. Since extreme returns tend to increase a market’s volatility (Brooks, 2002), we also tested whether index-wide institutional herding exhibits any differences between periods of “extreme” and “non-extreme” PSI20-returns. To that end, we partitioned PSI20-returns into two subgroups, namely “extreme” (lying over a single positive/negative standard deviation from the period’s average) and “non-extreme” (lying within a single positive/negative standard deviation from the period’s average) returns and calculated institutional herding on their basis.

Table 5.9: Index-wide institutional herding and index-volatility

Herding statistics for all stock-months (full sample period: 1/1/1997-31/12/2005). The herding statistic for a given stock in a given month is defined as: $H_{i,t} = [|B_{i,t}| / (B_{i,t} + S_{i,t}) - p_t] - AF_{i,t}$, where $B_{i,t}$ is the number of funds that increased their positions in stock i in period t ("buyers"), $S_{i,t}$ is the number of funds that decreased their positions in stock i in period t ("sellers"), p_t is the expected proportion of "buyers" in a period (t) relative to the total number of active funds and $AF_{i,t}$ is an adjustment factor designed to capture the random variations of the $[|B_{i,t}| / (B_{i,t} + S_{i,t}) - p_t]$ around p_t . The herding measure is calculated for each stock in each month, averaged across each month and then averaged across all months, according to the grouping for each test. Standard errors are in brackets. Note that: * = significance at the 10% level, ** = significance at the 5% level, *** = significance at the 1% level.

a) Index-wide institutional herding during periods of rising and declining index-volatility

	Rising	Declining	Difference (rising – declining)
Mean index-wide institutional herding measure	0.1126 (0.0069)***	0.1424 (0.006)***	0.0298 (0.0091)***

b) Index-wide institutional herding across different levels of index-volatility

	High	Mid	Low	Difference (high – low)	Difference (high – mid)	Difference (low – mid)
Mean index-wide institutional herding measure	0.1211 (0.0088)***	0.1144 (0.0081)***	0.1491 (0.0067)***	-0.028 (0.0111)**	0.0067 (0.0119)	0.0347 (0.0105)***

c) Index-wide institutional herding during periods of “extreme” versus “non-extreme” index-returns

	“Extreme”	“Non-extreme”	Difference (“extreme”-“non-extreme”)
Mean index-wide institutional herding measure	0.0901 (0.0096)***	0.1415 (0.0047)***	0.0514 (0.0107)***

As Table 5.9 indicates, index-wide institutional herding remains significantly (1% level) higher during “mild” periods compared to “extreme” ones; note also that it is statistically significant irrespective of whether returns are “extreme” or not.

Thus, these results seem to suggest that index-wide institutional herding appears to be statistically significant irrespective of the state of index-volatility, with its levels appearing significantly higher during periods of lower as opposed to periods of higher index-volatility. Moreover, in line with the above relevant findings from herding research, it assumes significantly higher values during periods of non-extreme versus periods of extreme market returns. These results appear to confirm our third hypothesis, namely that different levels of volatility are expected to bear significantly different effects over institutional herding at the index-level. One could interpret these results as the byproduct of a possible “rational” approach on behalf of fund managers, who may choose to trade on the basis of a widening public pool of information, rather than herd, if higher volatility is the outcome of a rise in the flow of information in the market (Mayhew, 2000). Alternatively, it might well be the case that less volatile periods promote institutional herding, since they may: a) be associated with a more definitive market direction upon which fund managers can herd and b) render the relative performance-benchmark for their evaluation less ambiguous, thus easier to follow.

5.7.1.d Index-wide institutional herding and index-direction

In hypothesis 4 we stated that different market-directions would be expected to bear significantly different effects upon institutional herding at the index-level.

To test whether this is the case, we first measured index-wide institutional herding for periods of rises and for periods of declines in the PSI20-index. The rises/declines of the PSI20-index are estimated here on a month-to-month basis. Table 5.10 shows us that index-wide institutional herding is significant (1% level) irrespective of the state of the index-direction. The mean index-wide institutional herding measure for periods of rises in the PSI20 (0.1362) is higher compared to periods of declines in the PSI20 (0.1196) indicating that funds tend to herd more when there is a rise in the PSI20. The difference between the levels of index-wide institutional herding between periods of rises and during periods of declines in the PSI20 was found to be significant at the 10% level, as the results from the Wald-tests in Table 5.10 indicate.

In light of the previous discussion regarding “extreme” versus “non-extreme” returns, we decided to test whether our results are subject to the influence of extreme returns. Thus, we partitioned PSI20-returns, into “extreme” positive/negative (lying over one positive/negative standard deviation from the period’s mean) and “non-extreme” positive/negative (lying between one positive/negative standard deviation from the period’s mean and the mean itself) ones. Results are reported in Table 5.10 and suggest that: a) “extreme” negative PSI20-returns are associated with insignificantly more index-wide institutional herding (0.0938) as opposed to “extreme” positive PSI20-returns (0.0852) and b) “non-extreme” positive PSI20-returns are associated with significantly (5% level) more index-wide institutional herding (0.1501) as opposed to “non-extreme” negative PSI20-returns (0.1311).

Similar results were obtained (Table 5.10) when we partitioned the PSI20-returns into three subgroups¹⁰⁹ based upon their level (“high”, “mid”, “low”), where index-wide institutional herding was found to be significantly higher (10% level) in the “mid”-subgroup (when the PSI20-returns are neither too high nor too low) compared to periods of “high”/“low” PSI20-returns. Note that index-wide institutional herding was found to be statistically significant irrespective of the subgroup tested upon.

Thus, these results seem to suggest that index-wide institutional herding appears to be statistically significant irrespective of the state of the PSI20-returns in general, with its levels appearing significantly higher when the PSI20-returns are positive, yet not extreme (as defined above). These results appear to accept our fourth hypothesis (namely that different market-directions bear significantly different effects over institutional herding at the index-level) and seem to favour the arguments put forward by herding theories regarding the role of agency/reputational concerns as a motive underlying the herding decision of less skilled/reputed fund-managers, in line with what has been mentioned in Section 5.2.2.d.

5.7.2 Discussion

The above presentation of our results regarding index-wide institutional herding at the level of the PSI20-index for the 1997-2005 period provides us with interesting insights into the herding tendencies of mutual funds. First of all, as is evident from what has been delineated thus far, institutional traders exhibit

¹⁰⁹ *All three subgroups are of equal size, i.e. upper, mid- and lower third of index returns.*

Table 5.10: Index-wide institutional herding and index-direction

*Herding statistics for all stock-months (full sample period: 1/1/1997-31/12/2005). The herding statistic for a given stock in a given month is defined as: $H_{i,t} = [|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|] - AF_{i,t}$, where $B_{i,t}$ is the number of funds that increased their positions in stock i in period t ("buyers"), $S_{i,t}$ is the number of funds that decreased their positions in stock i in period t ("sellers"), p_t is the expected proportion of "buyers" in a period (t) relative to the total number of active funds and $AF_{i,t}$ is an adjustment factor designed to capture the random variations of the $[|B_{i,t} / (B_{i,t} + S_{i,t}) - p_t|]$ around p_t . The herding measure is calculated for each stock in each month, averaged across each month and then averaged across all months, according to the grouping for each test. Standard errors are in brackets. Note that: * = significance at the 10% level, ** = significance at the 5% level, *** = significance at the 1% level.*

a) Index-wide institutional herding during periods of positive and negative index-returns

	Positive	Negative	Difference (positive – negative)
Mean index-wide institutional herding measure	0.1362 (0.0067)***	0.1196 (0.0066)***	0.0166 (0.0095)*

b) Index-wide institutional herding across different levels of index-returns

	High	Mid	Low	Difference (high – low)	Difference (high – mid)	Difference (low – mid)
Mean index-wide institutional herding measure	0.1260 (0.0087)***	0.1452 (0.0074)***	0.1135 (0.008)***	0.0125 (0.0119)	-0.0192 (0.0114)*	-0.0317 (0.0109)***

c) Index-wide institutional herding during periods of "extreme" positive versus negative and "non-extreme" positive versus negative index-returns

	"Extreme"		"Non-extreme"		Difference	
	Positive	Negative	Positive	Negative	"extreme" positive – "extreme" negative	"non-extreme" positive – "non-extreme" negative
Mean index-wide institutional herding measure	0.0852 (0.0156)***	0.0938 (0.0124)***	0.1501 (0.0059)***	0.1311 (0.0072)***	-0.0086 (0.02)	0.0190 (0.0094)**

significant herding tendencies at the level of the PSI20-constituents irrespective of the market conditions upon which their herding is tested.

This significant propensity towards institutional herding on PSI20-stocks may be attributed to factors related to the market itself that could be conducive to fund-herding. First of all, one should bear in mind that the Portuguese Stock Exchange accommodates a rather limited number of listed stocks; its Main market includes about fifty stocks, while the Alternative market about thirty. What is more, the market is highly concentrated, since as Vieira and Viera (2002) note, the five most liquid stocks on the Lisbon market represent roughly two-thirds of its total market activity. This, in turn, as Ho et al (2002) argue, implies the potential for relative illiquidity in the market with several stocks being thinly traded, a fact confirmed by Vieira and Vieira (2002) and Soares and Serra (2005). On the other hand, the Portuguese fund-industry maintains a rather highly concentrated structure, as we noted in Section 5.4.2. As a result, the Portuguese market is characterized by a limited number of stocks as well as a limited number of funds. In such a setting (and given that institutional - mostly indigenous – traders account for over two-thirds of the market-volume¹¹⁰), herding instincts may easily arise, since stock-screening on behalf of fund managers is alleviated, as they have a limited number of stocks to monitor. However, given the small population of funds, peer-screening will also be facilitated. Thus, there exists the potential of enhanced uniformity in the professional conduct across fund managers, more so in view of the agency-based concerns mentioned before with regards to herding. Herding on the performance-benchmark is alleviated in a highly concentrated

¹¹⁰ According to the January 2006 report on the composition of trade issued by the Portuguese Securities' Exchange Commission (Source: CMVM).

professional community, since any deviation from the latter is likely to confer a more personal stigma onto the deviants (Bikhchandani et al. 1992), notwithstanding the possible professional and reputational implications accruing in the aftermath of a potential negative performance. Therefore, such high concentration tends to magnify the impacts of the homogeneity (De Bondt and Teh, 1997) within the ranks of fund managers analyzed in Section 5.2.1, since peer-mimicking is greatly facilitated, thus allowing and, indirectly prompting, managers to monitor each other.

Our results allow us interesting insight into the trading pattern of funds, in general and in Portugal, in particular. First of all, although as we have said above there exists significant (1% level) index-wide institutional herding irrespective of the parameters upon which the latter is tested, it appears that institutional traders herd more when the PSI20 undergoes through relatively less intense conditions. Institutional herding on the premises of the PSI20-index constituents assumes its highest values when: a) index-wide market-herding levels are low/declining, b) index-wide trading volume levels are low/average or declining, c) index-volatility is low/declining and d) index-returns are non-extreme (and positive).

Why funds may behave in such a fashion is not directly obvious. Non-intense market conditions reflect less uncertainty and may point towards a clearer market-direction (Hwang and Salmon, 2004), upon which funds may herd. A relevant explanation for this may be that the reference-benchmark of the performance-evaluation of fund-managers may be less ambiguous during less intense market periods compared to turbulent ones and, as a result, easier to follow. It is possible that less volatile market conditions may generate less informational signals (Mayhew, 2000) upon which funds can trade, thus providing

less possible options for them to choose; the latter may facilitate the development of cascades (Banerjee, 1992; Bikhchandani et al, 1992). Finally, empirical findings (Choe et al, 1999; Lobao and Serra, 2006) also provide some evidence in support of lower institutional herding levels during more intense market conditions. Thus, our results indicate the presence of significant institutional herding in the Portuguese market which can be interpreted through existing theoretical tenets of herding research.

5.8 Conclusion

A substantial portion of existing Finance research (Bikhchandani and Sharma, 2001; Hirshleifer and Teoh, 2003) has demonstrated that there exists both theoretical, as well as empirical evidence in support of the case of institutional herding. The latter has been tested in various market settings and upon various parameters in an attempt to assess its significance. We contribute to this literature by testing for the impact upon institutional herding of various market conditions (market-wide herding, volume, volatility and market-direction), the association of which with institutional herding has received rather scant attention in the relevant literature. For consistency reasons, we base the enumeration of both the institutional herding as well as the aforementioned market-conditions upon a specific market-index. To the best of our knowledge, institutional herding has never been tested on the basis of those premises.

Our tests are conducted on the basis of a unique institutional holdings' database from the Portuguese Stock Exchange and aim at measuring institutional herding on the premises of the historical constituents of the PSI20-index during the 1997-2005 period. Results indicate the presence of statistically significant

herding on behalf of fund managers irrespective of the state of the market and whose levels are higher during periods of less intense market conditions. More specifically, we found higher institutional herding levels during periods when: a) index-wide market-herding levels are low/declining, b) index-wide trading volume levels are low/average or declining, c) index-volatility is low/declining and d) index-returns are non-extreme (and positive). We also showed that, although differences in the direction and volatility of the market can lead to significantly different effects over institutional herding, this is not the case with market-herding and the volume of trade.

We have illustrated how these results can be interpreted through existing herding theories, mostly related to agency-related considerations on behalf of fund managers and we also demonstrated how the market's environment itself may tacitly promote these considerations.

Chapter 6

Concluding Remarks

The thesis present aimed at delineating the role of a variety of market-features and conditions over herding and feedback trading over time within as well as across markets. We consider the research undertaken here as contributing towards the better understanding as to which factors promote or inhibit the manifestation of trading strategies, in general and herding with feedback trading, in particular. As the impact of herding and feedback trading in securities' markets has been widely documented in the Finance literature in both analytical as well as empirical terms, our research attempts to reverse the argument: in other words, instead of focusing on the impact of those strategies on the market, we examine the impact of the market upon them. This is an element that has been rather scarcely investigated in the relevant research and, as a result, our work produces useful evidence towards that direction. Concurrently, our thesis extends the debate over these two trading patterns by suggesting an alternative approach towards their study.

Following the review of the literature in Chapter 2, Chapter 3 delves into the world of heterogeneous agents' models in order to assess the presence of feedback trading in various market settings. We employ an existing such model, where rational traders interact with their feedback peers and expand it by adding an extra trader-type, whose feedback trading is conditioned upon the violation of a

threshold. Given the feedback nature of that trader-type, we tested for its significance in several markets with differences in their heterogeneity levels, as reflected through the participation-levels of various investor-types. The idea here was the following: the more heterogeneous a market is the more investor-types it is capable of attracting and, thus, the more investment strategies it may have the potential of accommodating. Our results pointed towards that direction, thus confirming that more heterogeneous markets have the potential of accommodating a larger array of trading strategies; a second reading of those results would also suggest that various feedback strategies have the potential of materializing more significantly in more open market environments.

Our work in Chapter 3 does not only contribute to the debate surrounding feedback trading by exploring its presence in different market settings. We have (perhaps, persistently) noted in this thesis that feedback trading is an umbrella-term and as such bears no single trading-expression. Given that, our novel trader-type constitutes an extra possible type of feedback trading, thus further adding to the modeling of that mode of trading.

In Chapter 4 we explore herding across various markets on the premises of several market-specific features, whose relevance to herding we theoretically establish in the outset. Our results confirm that herding is higher in markets with capital gains' taxes, yet fail to provide any support for the conjectured impact of the introduction of short-sales and index-futures upon it. Although based upon a relatively small sample of markets, our evidence contributes to the existing literature on herd behaviour by conditioning the presence of the latter upon specific elements of a market's structure capable of affecting it.

Finally, in Chapter 5 we focus on the herding of a specific subset of investors, namely fund-managers. We investigated institutional herding in the Portuguese market on the premises of the constituent-stocks of the market-index (PSI20), thus enabling ourselves to gain an accurate picture of its presence at the index-level. To the best of our knowledge, this is the first time that institutional herding has been measured exclusively at the level of a market's index. What is more, in view of that, we also tested for the impact upon the presence of funds' herding of certain index-properties reflective of market-conditions capable of affecting herding and found that the significance of the latter remained unchanged irrespective of the market conditions tested upon. We also illustrated how the high concentration levels of both the Portuguese market as well as the Portuguese funds' industry could be considered as contributing to the significant institutional herding levels observed. Interestingly enough, we found that Portuguese fund managers tended to exhibit higher herding tendencies during periods typified by relatively non-intense market-conditions and we demonstrated how this could be ascribed to herd-related, agency concerns.

The results of our research have the potential of being of certain interest to both market participants as well as policymakers alike. With regards to the former, our evidence demonstrates whether the presence or absence of specific market features is capable of affecting the manifestation of herding and feedback trading. This is useful both in case one intends to adhere to those patterns as well as in case one wishes to formulate a strategy to take advantage of them. Also, our evidence on high levels of significant institutional herding in a highly concentrated market environment might also constitute a useful input in the decision-making of market participants who trade in markets with similar

structures. What is more, the preoccupation in Chapters 4 and 5 with herding at the level of the top-capitalization indices of various markets raises interesting issues *per se* in terms of trading, as all of these indices are the underlying subjects of index-futures' contracts; consequently, the evidence produced in this thesis is expected to be of some interest to that part of the investment spectrum.

From a policymaking point of view, our research provides evidence for the first time of the impact of the regulatory environment over herding and feedback trading. Given the treatment of those two by the popular literature as the culprits underlying abnormal market phenomena, their research on these premises helps delineate whether it is the market environment itself that may tacitly “grandfather” their manifestation. In Chapter 3 we show how the expression of an hypothetical feedback trading pattern is found to be more significant in relatively liberal market settings, while the findings of Chapter 4 indicating reduced herding in markets with zero capital gains' taxes may also be reflective of the potential link between capital gains' taxes and herding. What is more, our results from Chapter 5 should provide a clear indication of the effects of high market concentration over the presence of herding in the market on behalf of mutual funds. As a result, our findings seem to suggest that the significant manifestation or not of specific trading patterns may actually be the outcome of the market environment and its relevant regulatory structures.

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We now turn to the implications of our work for future research by beginning from the issues dealt with in Chapter 3. As we also suggested there, the possible avenues for research as regards various feedback trading patterns are hard

to enumerate, given the multiple possible facets of the latter. In terms of “threshold trading”, it is our understanding that it constitutes a conditional feedback trading pattern that can be tested on the premises of a large array of conditioning factors. As a result, future research on threshold-trading could resort to the testing of many more indicators, both volume- as well as non-volume-based. What is more, the inclusion of a larger variety of markets would provide us with wider evidence over the presence of threshold- trading across various market-settings. Research regarding herding could be expanded in a similar fashion, i.e. through testing for herding in more markets; in addition to that, herding could be tested on the premises of other market features and conditions capable of bearing an effect over it. What is more, research on the impact of market-factors over investors’ behaviour could well be expanded to include other expressions of behavioural trading beyond herding and feedback trading, such as, for example, the disposition-effect.

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